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INTRODUCTION

Over the past two decades, the hardware industry has followed Moore's law resulting in faster processors using smaller and more power efficient transistors. This shrinkage of size and increase in processing power has caused an explosion in the number of embedded systems for various applications with the most prominent among them being mobile phones. However, devices used in the medical field require significant processing capabilities because of the vast amount of data processing involved in acquiring physiological signals. It is only recently that it has become feasible to utilize this increased processing power for embedded and cyberphysical systems supporting biomedical applications. Cyberphysical systems differ from traditional embedded systems in the fact that there are a number of processing elements and sensors which coordinate amongst themselves to accomplish a task. In cyberphysical systems, the emphasis tends to be on the interaction between the computational and physical elements.

One of the relevant studies in this field focuses on providing Body Sensor Networks by utilizing modified wireless sensor network platforms for biomedical applications [1]. The hardware platforms consist of a processing element with integrated sensors (e.g., temperature sensors, accelerometers) and a wireless transceiver. Such sensor networks are employed to monitor patient activities, record the relevant information, and initiate actions based on the information collected. An example of such a system is the SMART Attire or SATIRE which provides wearable computing to monitor activities of a person [2].

While such systems deal with non-critical data collected from the human subjects, a more difficult challenge arises when collecting accurate physiological data, which is essential for correct diagnosis and to initiate appropriate feedback action. Thus, ensuring reliable data processing and automated decision making is extremely important to trust the conclusions drawn from the data.

In this project, we designed and prototyped an embedded system that is capable of collecting data from physiological sensors (e.g., EEG, oxygen saturation, and accelerometers) in a synchronous manner and analyzing the data in real time to detect abnormalities in the waveforms and warn the user in the due time. The contributions of this work include:

1. The architecture of a low cost, power efficient biomedical embedded monitoring and diagnostic device that is capable of collecting and analyzing data in real time.
2. The implementation and evaluation of a prototype device based on the above architecture designed to detect conditions such as traumatic brain injury (TBI), seizures, and cognitive decline.

Background

Prerecorded human EEG recordings, which were free of artifacts, were used in this research to provide a foundation for evaluating the performance of the developed system prior to human subject use. Since most of the EEG data available pertain to seizures, we discuss the work related to detection and analysis of seizures.

Hively et al. under the CRADA hardware and software setup utilizes non-linear techniques in EEG forewarning equipment [3]. This method works by using a three dimensional phase space representation of the collected data. Seizure occurrence is predicted from the dissimilarities between the distribution function for the non-seizure waveforms and seizure waveforms. However, this device is exclusively limited to detecting seizures. Environmental conditions under which the patient is operating are not taken into account. This considerably limits the application space of the device. Verma and colleagues focus on small footprint SoC solutions for continuous patient EEG monitoring and seizure prediction devices [4] [5] [6]. Considerable work has been done in the area of embedded devices for collecting EEG data with reduced artifacts [7] [8]. Such devices or solutions focus only on the data collection aspect of the EEG data with almost no processing carried out in real-time. Reference [9] below describes a real-time EEG processing device based on TI's signal processing platform which decomposes the collected EEG data into various frequency bands for visualization purposes. However, the power consumption of such a device can be quite high limiting its use in a power constrained embedded environment.

The system prototype designed in this project differs from the systems described above in the ability to collect EEG, oxygen saturation, and heart rate data in real time and detect abnormalities in the data before alerting the user and a remote logging base station. The device uses a standard Commercial Off the Shelf (COTS) power-efficient device (e.g. microcontroller) to realize this goal, in addition to several inexpensive and non-invasive sensors. The cost-effectiveness and adaptability to several application scenarios make our solution quite unique.

BODY

Monitoring brain activity has been useful in detecting and explaining brain injuries and disorders in individuals such as traumatic brain injury and cognitive decline. Two commonly used technologies for this purpose are pulse oximetry and electroencephalography [10] [11]. One purpose of this research is to show that by using these technologies in embedded monitoring systems, one can improve the research, monitoring, diagnosis, and treatment of brain injuries and disorders.

Electroencephalogram (EEG)

For many years, EEG has been used extensively to monitor brain activity. One difficulty with EEG is that only trained clinicians are able to interpret EEG waveforms and identify abnormalities. Quite recently, however studies have focused on utilizing digitized EEG data to extract useful information. This is called Quantitative EEG (QEEG). QEEG helps to transform the waveforms into frequency bands using Fast Fourier Transform or other filtering techniques. Once a pattern in such a scheme is associated with an abnormality, there exists a mechanism for automated decision making. Using QEEG, researchers have shown that some of the important values are alpha-theta ratio, theta-relative power and coherence [12][13]. Alpha-Theta ratio is explained in Section VI and Coherence is explained in Section IX.

Pulse Oximetry

Oxygen saturation (SpO_2) can be measured using pulse oximetry. One benefit of pulse oximetry is that it is non-invasive. Studies have shown that oxygen saturation is an efficient indicator of neurological outcome in patients with traumatic brain injury. In normal adults, oxygen saturation remains close to 100%. Cognitive ability and normal brain functions begin to be affected when oxygen saturation is below 90%. Very poor neurological outcome is expected when oxygen saturation is below 70% [14] [15]. In some patients with epileptic seizures, oxygen saturation levels have been shown to drop below 90%, while some drop below 70%, soon after seizure onset [16].

Traumatic Brain Injury (TBI)

TBI is a complex injury with a broad spectrum of symptoms and disabilities, the impact of which on a person can be profound and devastating. TBI may be missed during the early stages of diagnosis when the focus is on critical injuries or ones with visible symptoms. If TBI is associated with loss of consciousness and confusion for less than 30 minutes, it is generally classified as mild and if it lasts for more than 30 minutes and is associated with memory loss, it is categorized as severe. According to the United States Center for Disease Control and Prevention, there are approximately 1.5 million people in the US who suffer from TBI each year [17]. Early diagnosis of TBI can go a long way in significantly reducing the impact of the injury.

TBI is caused by open head injuries which include bullet wounds, closed head injuries which result from falls, motor vehicle crashes, chemicals, deceleration injuries or hypoxia (lack of oxygen). The two causes which are of importance in this work are deceleration injuries and hypoxia. Deceleration injury refers to the rapid movement of the skull through space followed by immediate deceleration which causes the brain to move inside the skull. Different parts of the brain move at different speeds because of their relative lightness or heaviness. When the brain is slammed back and forth inside the skull, it is alternately compressed and stretched because of its gelatinous consistency. If the impact is strong enough, axons can be stretched until they are torn. This is called axonal shearing and the neuron dies. After a severe TBI, there is massive axonal shearing. The other cause that is of significance is hypoxia or lack of oxygen. This condition may be caused by heart attacks, drops in blood pressure and being present in a low oxygen environment. This type of TBI can cause severe cognitive and memory defects.

Transient explosions on the battlefield result in blast injuries that are polytrauma in nature. That is, along with physical wounds addition injury can include cognitive and communication impairments related to TBI (traumatic brain injury), swallowing impairments, aphasia, motor speech impairment, hearing loss, and other medical conditions. As of March 8, 2007 23,417 traumatic combat injuries have been reported [18]. Approximately 51% of returning wounded, or 11,852, had been exposed to blast injuries, the most common being from Improvised Explosive Devices (IEDs). In addition, military personnel are surviving beyond the acute phase of blast injuries due to improvements in body armor, battle-site and acute trauma care. They are surviving with new, multiple and complex patterns of injuries including traumatic brain injury, traumatic limb amputation, nerve damage, burns, wounds, fractures, vestibular damage, vision and hearing loss, chronic pain, mental health, and adjustment.

TBI poses the great risk because it may be caused by all four mechanisms (primary, secondary, tertiary and quaternary) of blast injury. Blast over-pressurization exposure adds significant complexity to the profile of blast cases with TBI. First responders and medical teams need to have information on the level of blast exposure to the brain as well as critical data regarding the physiological functioning of cortical systems. Recording blast events and physiological responses using smart nanotechnology embedded into helmet supporting structures would provide vital information for first responders and forward medical teams. The utilization of a combination of sensor inputs designed to monitor brain function, pre and post blast exposure, may provide (i) insights into prediction of recovery from battlefield blast exposure and traumatic brain injury and (ii) information for in-depth clinical diagnostics and rehabilitation in a polytrauma rehabilitation center and for in the home long term care for individuals with TBI/PTSD (Post Traumatic Stress Syndrome). These new bio-sensing monitoring technologies help build a continuum care for military personnel and as an in-field device form a platform of epidemiological data gathering on TBI occurrence. A depiction of this continuum of care is provided in Figure 1.

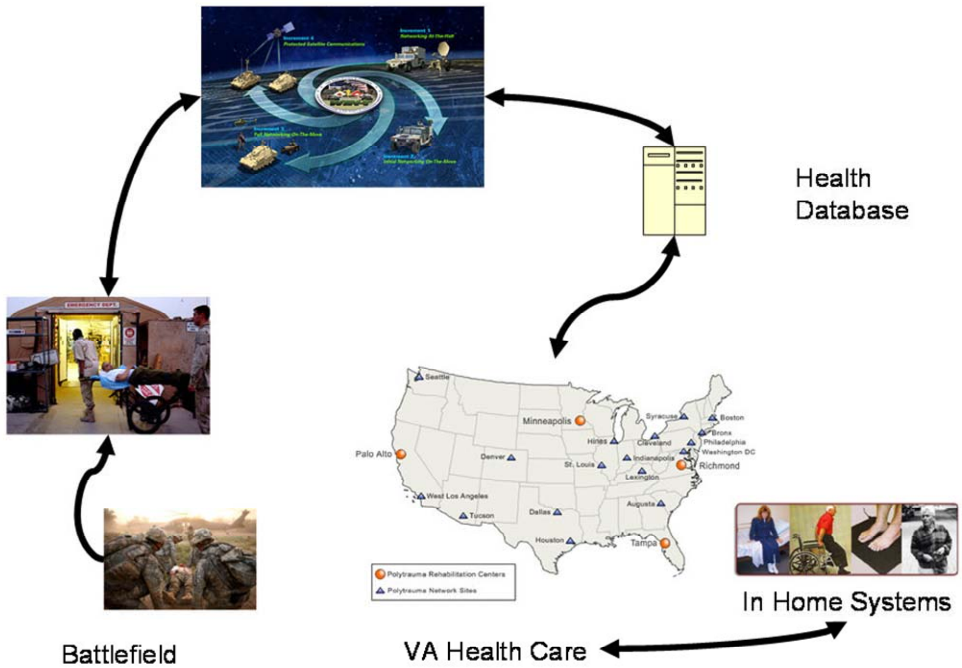


Figure 1: Pervasive Monitoring Systems for TBI/PTSD - A Continuum of Care

Cognition Decline

Recent research on mildly demented patients with Alzheimer's disease revealed slowing of the EEG, i.e. higher theta power, less beta power and lower peak frequency, were linked to cognitive decline on the CAMCOG [12]. Similar results were confirmed by [19] using change in GDS score as an indicator of cognitive decline in subjects with subjective memory complaints. Increases in theta power, slowing of mean frequency and changes in coherence among regions were observed at baseline in subjects who declined after 7-9 years follow-up. Cross-sectional studies in elderly with different levels of cognitive impairment have also reported correlations between EEG spectral parameters, i.e. higher theta activity during rest and lower alpha activity during memory activation and decreased GDS scores [20].

Unlike the painfully obvious losses seen in Alzheimer's disease and other forms of dementia, subtler changes in cognitive functions such as memory, attention, perceptual and motor skills, language, and problem solving are common but not universal in the elderly. In addition, some older adults exhibit "mild cognitive impairment" yet not enough to merit a diagnosis of dementia. Age related cognitive decline usually occurs gradually. Sudden cognitive decline is not a part of normal aging. When people develop an illness such as Alzheimer's disease, mental deterioration usually happens quickly. In contrast, cognitive performance in elderly adults normally remains stable over many years, with only slight declines in short-term memory and reaction times.

Studies of healthy older adults have found a wide range of prevalence of cognitive decline, from less than 10 percent to more than 40 percent of those aged 60 or older, with incidence increasing with age. The broad range may reflect, in part, a lack of consensus about how age-related cognitive decline should be defined, measured, and described [20].

Embedded Monitoring Systems

The research relating to cognitive decline and traumatic brian injury underscore the need for advanced embedded monitoring systems that are robust, secure, relatively non-invasive for use in a number environments, e.g. at home, in a residential facility, or hospital. Our vision of such trustworthy, pervasive health technologies is described in Figure . Figure shows the conceptual framework and core architecture that permits the flexible integration of simple, low-cost systems that obtain their decision-making and communication functions from the existing infrastructure.

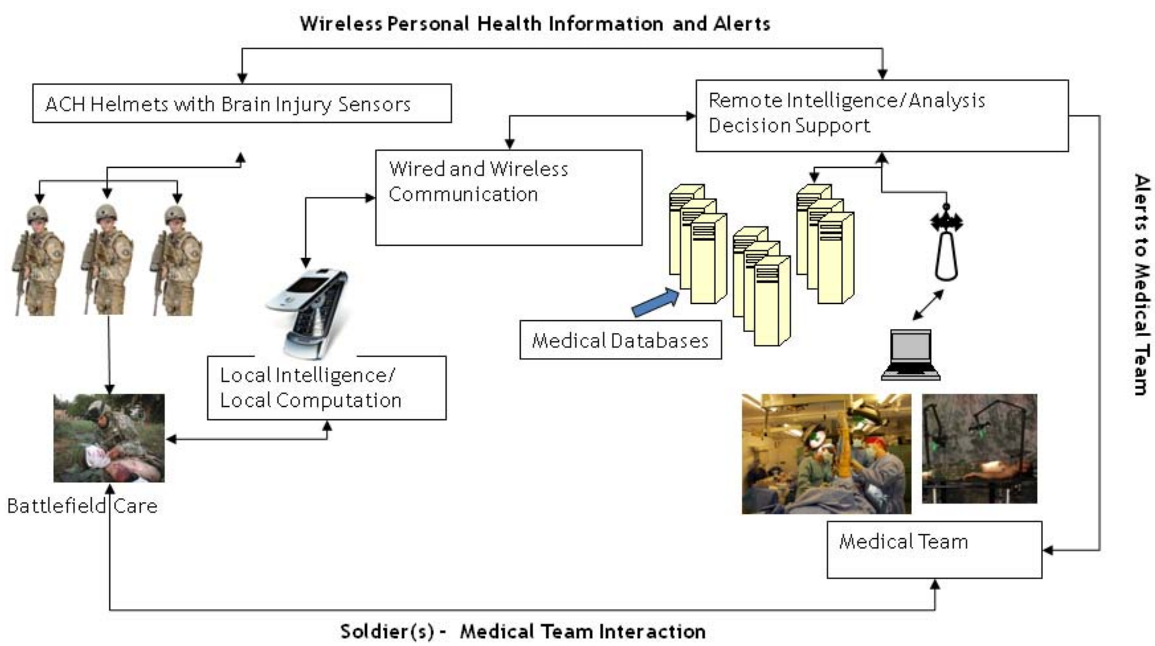
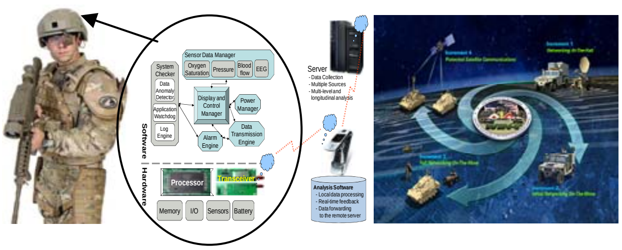


Figure 2: Core Architecture

The above core architecture is intended to represent the key design philosophy of our engineered system, which includes:
A multi-sensor network consisting of cost-effective helmet based nano-sensors that communicate with personal health databases and field hospital medical teams.
Local intelligence where preliminary signal and data processing occur. The local intelligence module can provide immediate feedback to caregivers and patients, and also determine what information to transmit or draw from remote decision-support systems.
Secure, private, and trustworthy networking capabilities that leverage novel distributed security and privacy algorithms and hardware for low-cost sensors on powerful networks.
Remote intelligence/decision-support that interfaces to relevant information for decision and control.

The result of applying our core architecture to monitoring and management of cognitive decline are low-cost, highly trustworthy systems that can be easy adapted to the needs of individual users.

Research has indicated that level of blast pressure, head acceleration and electro-encephalographic (EEG) waveform changes are significant indicators of potential traumatic brain injury [21][22]. The continued exposure to potentially concussive forces due to the blast pressure created by improvised explosive devices has motivated our development of a multiple set of physical and physiological recording sensors embedded in the pads of the Advanced Combat Helmet (ACH). These sensors are securely connected to a small processing device within the helmet. The fundamental task for this embedded monitoring system is to provide alerts signaling changes in cognitive activity to the individual soldier as well as pervasively to functional groups of soldiers and medical/material command as depicted in Figure 3.



(b)

Figure 3: Embedded System Schematic a) Soldier Level b) Theatre Level Information Systems

The design of a multisensor system embedded in an advanced combat helmet is presented that is capable of real time tracking of physiological signals (EEG, blast pressure, head acceleration, oxygen saturation and heart rate) and facilitating a reliable and dependable decision making process that provide alerts for potential traumatic brain injury. The cyperphysical system focuses on the use of heterogeneous sensors within the helmet pads and a processing element for real time algorithmic processing.

SYSTEM DESCRIPTION

In this section, the various modules involved in the prototype system are discussed. The developed prototype enables direct helmet based recording and execution of reliable algorithms that record blast pressure, frontal qEEG, SpO_2 and head acceleration. The sensed data indicates the potential presence of trauma brain injury while simultaneously providing vital sign information profiles. Integrating magnitude of blast with predictive algorithms regarding the level of blast injury provides early warnings of soldier status. Gathered information can be available immediately to first responders using a cell-phone-like handheld device that will also be used to port the information directly to medical staff, military medical databases, military hospitals and polytrauma rehabilitation centers.

Figure 4 shows the locations of our sensors embedded within the pads of the ACH to record blast pressure, head acceleration and rotation, frontal EEG, SpO_2, and heart rate.

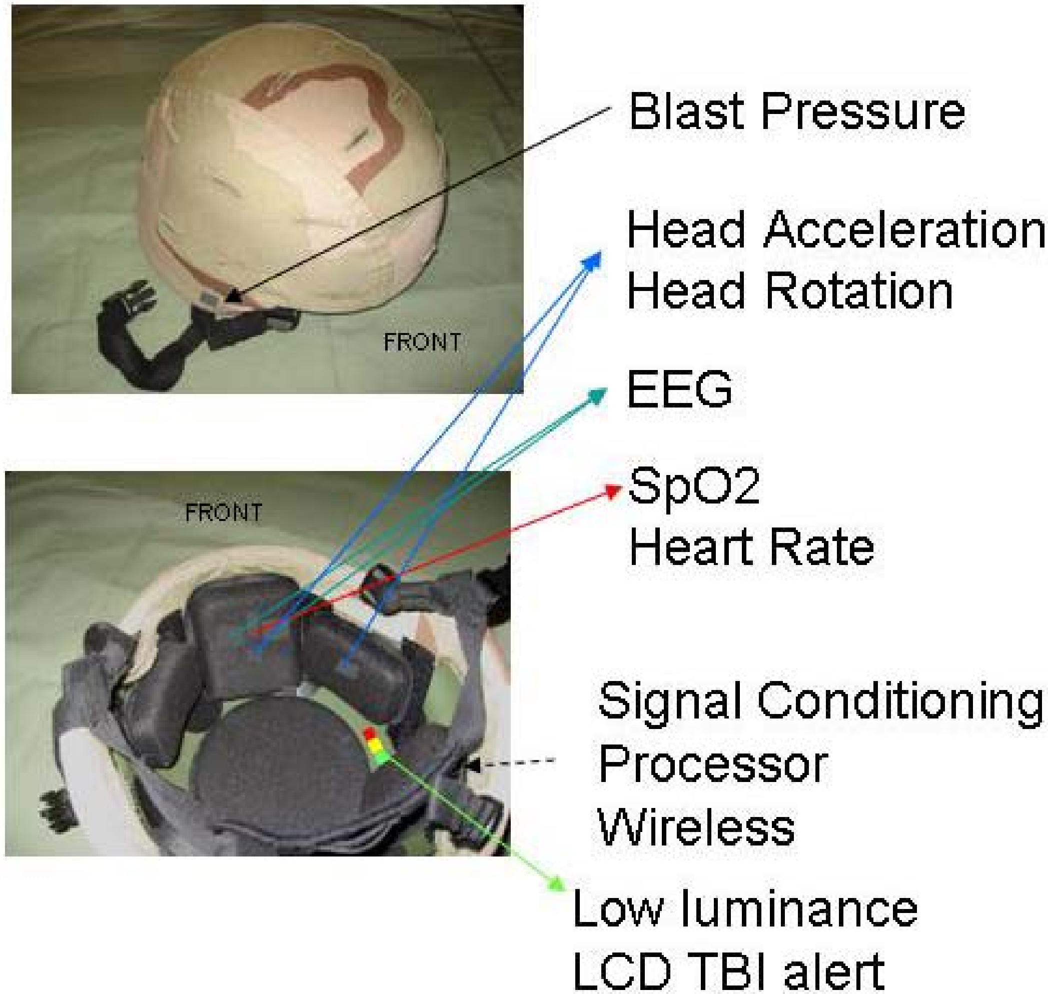


Figure 4: Helmet with embedded sensors

Accelerometers

Accelerometers help capture the acceleration of an object in terms of an analog voltage which is directly proportional to the dynamic acceleration experienced by an object. In other words, a device at rest will indicate a value of acceleration equal to 9.8m/s2 or 1g along the vertical axis. However, in most cases, the value of acceleration would be non-zero along the other axes, which makes it necessary to calculate the baseline values of acceleration for a body at rest. The accelerometers are part of this design for its use in applications where the risk of injury is related with an action that results in quick movement of the person or object. (One such scenario is described in Section 8.) The accelerometers used in this system are MEMSIC's heat transfer based micrometer sized devices which offered significantly improved performance over traditional proof mass based systems and have a shock rating of over 50,000g. The prototype used models of the device with a higher sensitivity, 500mV/g and range of +/-1.7g at 3V. This is to obtain a measurable voltage with reasonable movement under the lab's testing conditions. Accelerometers with lower sensitivity can be used when the total acceleration to be expected is higher. Tri-axial accelerometers are used in this prototype.

Oxygen Saturation and Heart Rate Monitor

Oxygen saturation measures the percentage of hemoglobin binding sites in the bloodstream occupied by oxygen. The device used to perform the calculation is called a pulse oximeter. It relies on the light absorption characteristics of saturated hemoglobin to determine the percentage of oxygen contained. The typical method of measurement consists of using a sensor containing red and an infra-red or near infra-red light emitting diodes. The diodes are placed in contact with the skin along with photodiodes to determine the amount of light from the two sources which are absorbed and reflected. This data is used to compute the oxygen saturation. As mentioned earlier, oxygen saturation under normal conditions is close to a 100%.

The wave patterns, picked up by the photodiodes, display an ac value with a dc component. As can be intuitively understood, since we are computing the blood oxygen saturation levels, the frequency of the ac component gives us the heart rate of the individual. Hence, most pulse oximeters are capable of computing the heart rate. Due to the availability of commercial devices which are capable of computing these values accurately with minimal artifacts, a commercial product was used for our purpose. The OEM III module from NONIN is used in this study. The Puresat Signal® processing technique employed in the module is ideal for use in motion and low perfusion environments. This approach provides more reliable readings over simple microcontroller based pulse oximetry solutions. The NONIN sensor provides a 4 beat average heart rate and a 4 beat average SpO_2 values.

EEG Electrodes

EEG refers to the measurement of the electrical activity of the brain and is recorded by placing multiple electrodes on the scalp. Electrode locations and names are specified by the International '10-20' system ensuring consistency in the naming convention. In most clinical applications, 19 electrodes along with two reference electrodes are used. Most of the EEG data used in this study is obtained from patients suffering from seizures. With regard to seizures, an important term is the Ictal period. Ictal period is the duration of the actual seizure and the EEG reading during this period is the ictal EEG. The time shortly before and after the seizure are called Pre-Ictal and Post-Ictal respectively. The time between two seizures is the Inter-Ictal period and for epileptic patients, most of the EEG readings correspond to this period.

A significant amount of seizure activity is observed in the frontal region of the brain (i.e. in the electrodes placed on the forehead) and hence, most of the study and detection schemes used in this research focus on Fp1 and Fp2 electrodes. The waveforms observed on the two electrodes are quite similar. This can be expected because of the symmetrical placing of the two electrodes on the forehead. Hence for our analysis, we focus on the signal from the Fp1 electrode. One recent study on EEG characteristics related to depressive disorder conducted with data collected during the ictal period of the seizure observed maximum change on the Fp1 electrode [23].

As mentioned previously, rhythmic activity within the different bands of the EEG frequency spectrum are known to have biological significances and this is utilized in the detection scheme. The different EEG bands are outlined in Table 1.

Table 1: Different Frequency Bands of EEG Signals

Band Frequency	Range
Delta	1 – 3 Hz
Theta	4 – 7 Hz
Alpha	8 – 12 Hz
Beta	13 – 24 Hz
Gamma	24 – 70 Hz

To develop and test the prototype, we utilize EEG signals generated by an EEG simulator (Grass Technologies, Model EEGSIM). The simulator has a patient's ictal EEG stored on a PROM (Programmable Read Only Memory) which is replayed every 60 seconds. Several models of the EEG simulator corresponding to different types of EEG waveforms are available.

Microcontroller

The central processing element of the device is a microcontroller which is capable of collecting the data from the different sensors and processing them. In addition to the processing power, limiting the power consumption was an important constraint. The MSP430FG4618 from the MSP430 line of microcontrollers was chosen for this purpose. The microcontroller has 116KB of flash memory and 8 KB of RAM. The important peripherals included in the microcontroller are the Analog to Digital Converter, the Serial Communication Interface and the Serial Peripheral Interface. It also features the support for an LCD module, which can be used to provide visual feedback to the user should the application demand it. A development board with the microcontroller was used for the prototype development. A schematic of the board is provided in Figure 5.

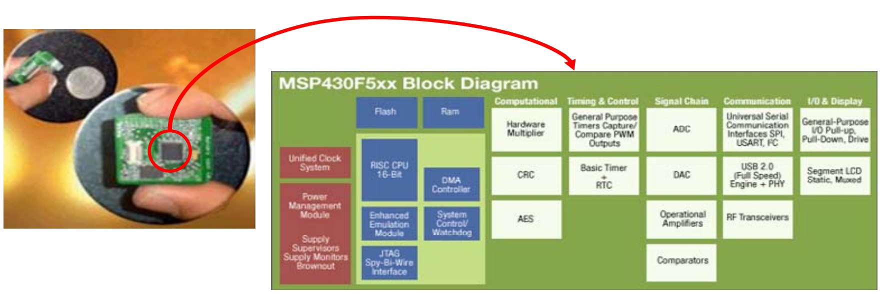


Figure 5: Prototyping Board with the MSP430 Microcontroller

Wireless Interface

The device has been designed keeping in mind the desire to communicate the results of the monitoring procedure to a base station which is capable of logging the results periodically or to communicate the result to another piece of equipment. For this purpose, a wireless communication interface was also setup. The Chipcon CC2500 module from Texas Instruments is used for this purpose. It is a low power and low cost transceiver used for wireless communication in the 2.4GHz ISM band based on the ZigBee protocol. It is capable of transmitting in packets of 64 bytes along with support for a low power sleep mode operation.

SYSTEM OPERATION

In this section, the operation of the device is explained. The signals from the sensors, namely the accelerometers, pulse oximetry module, and EEG electrodes are first processed the analog to digital converter (ADC) before being collected by the microcontroller. The signals from the accelerometers can be low pass filtered if desired, but the dc component of the waveform should not be eliminated to obtain a higher analog voltage of acceleration. Low analog voltages can suffer attenuation resulting in faulty decision making. Two dual axes accelerometers or a single tri-axial accelerometer can be used to obtain acceleration along the X, Y and Z directions. The microcontroller is not capable of sampling negative voltages and so, to facilitate that, the EEG signal is level shifted by a dc value before being fed into the amplifier. Since the EEG signal levels are typically in the range of 5- 50uV, a high impedance biomedical signal amplifier is used to amplify the signal by a value of the order of a few thousands. The amplifier used, supports variable gains from values of 1700 to 5000. A value of 2000 was used for our experiments. The amplified output is fed into the microcontroller. The level-shifting voltage value used is also sampled by the microcontroller. The pulse oximetry module is interfaced with the microcontroller through the serial port and the oxygen saturation and heart rate values are obtained in digital format and so, no processing is required.

The frequency at which these signals are sampled depends on the frequencies of interest. The frequencies of the EEG signals and accelerometer waveforms influence the minimum sampling rate. Since the accelerometer readings are instantaneous measurements of acceleration and since no frequency band decomposition is carried out, we will focus on the frequencies of interest in the EEG signals which are in the 1 – 70 Hz. However, since the metrics we utilize rely only on information in the alpha and theta bands, the maximum frequency in the bands of interest is 12 Hz and so the sampling frequency should be greater than 24 Hz. A value of 64 Hz is chosen. Sampling within the microcontroller can be carried out by using timers to trigger the conversion process within the ADC or by setting the ADC to continuously sample the data from the sensors and then using timers to read the digital values at the sampling frequency. The former approach is used as it is more consistent with the idea of sampling. Two timers are used to generate a 64 Hz waveform which is used to enable conversions within the ADC module.

Since we need to extract information contained within the various frequency bands of the EEG waveforms, we use 21 point symmetric Finite Impulse Response (FIR) filters. The coefficients for the filters are pre-computed using MATLAB and saved in the microcontroller. A 21 point value was chosen as a tradeoff between precision and computational space. A higher precision filter could have been used at the expense of higher storage space requirements (each coefficient is a floating point value) without considerable improvements in the quality of the filtered output. Another important consideration is the epoch or time window over which the calculations are made. While it is desirable to make decisions over a relatively long period of time, the memory space requirements impose a burden because of the limited memory space within the microcontroller. A value of 12 seconds was chosen to be length of the time window. While the measurements made are dependent on the length of the time interval, eventually a comparison is carried out with reference to a baseline value computed over the same time interval for every individual. This offsets the impact of the length of the selected time window. All the metrics are computed over the duration of this 12 second window.

The entire system operates as shown in Figure 6. Once the module is switched on, it computes the baseline/at rest values for metrics pertaining to each of the sensor values. Then the module goes into a monitoring mode, which can be continuous or event-triggered. In the continuous monitoring scheme, data from the sensors are collected and metrics are computed on a continuous basis. In the event-triggered monitoring scheme, an external event is used to trigger the monitoring process. One example of such an event could be an accident resulting in sudden acceleration of the individual which would show up as a spike in the accelerometer reading. This spike can then be used to shift the module in the continuous monitoring mode. Such a scheme can be used in extremely power-constrained environments. Once the data is obtained, the results of the computation process are then wirelessly transmitted to the base station which is another MSP430 node connected via the serial port to the PC. A Perl program reads the data from the serial port and logs the data into a MySQL database.

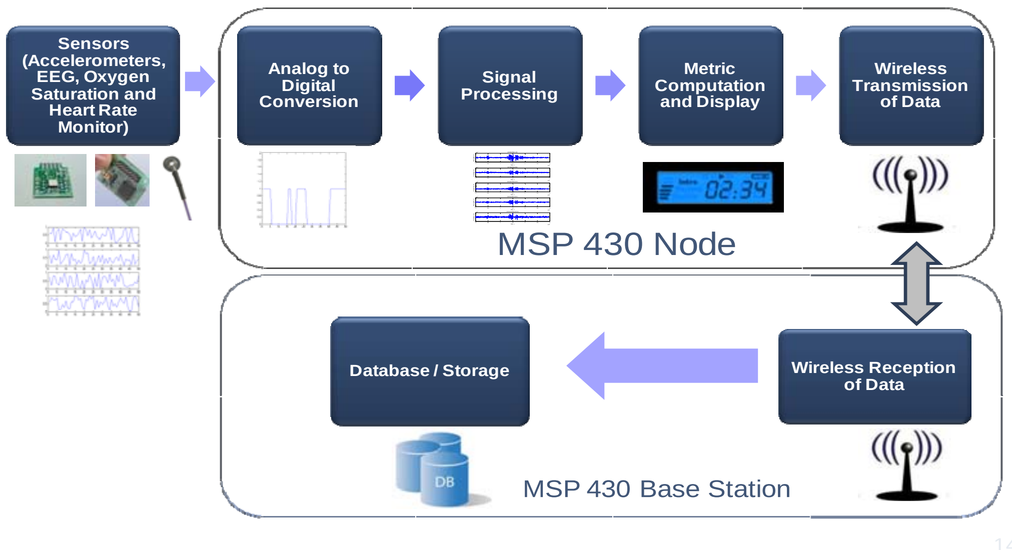


Figure 6: Working of Biomedical Monitoring System

EVALUATION

The EEG data on which analysis is carried out originates from a person who suffered a seizure. One minute of ictal data is available using the simulator. The primary indicator of a seizure is an increase in the amplitude of the low frequency theta waves with a simultaneous decrease in the amplitude of the higher frequency alpha waves. Since power is directly proportional to the square of the amplitude, the power contained in each frequency band can be computed over the duration of the data collection period (i.e., 12s in our study). The metric that is used to detect abnormalities in the EEG waveform is therefore, the alpha-theta ratio.

The alpha- theta ratio can be defined as the ratio of the power in alpha frequency band to the power in theta frequency band. When a seizure is observed, the alpha-theta ratio for that individual should be lower than the base/normal value established for that person. Figure 7 shows the alpha wave during the 12 second pre-ictal and ictal periods and Figure 8 shows the theta wave during the same periods. Although, the ictal period shows a minor increase in the alpha wave amplitude, the theta wave amplitude increases almost 3 fold resulting in an overall decrease in the alpha-theta ratio.

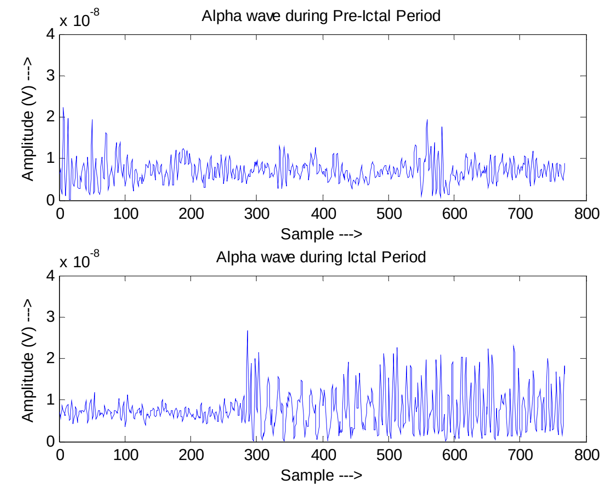


Figure 2: Alpha wave during Pre-Ictal and Ictal Periods

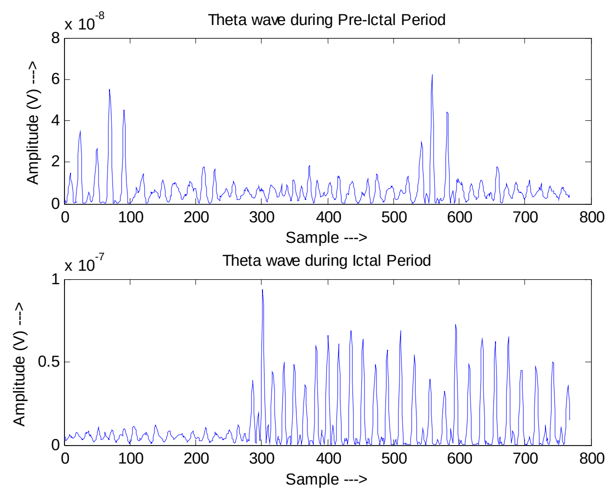


Figure 3: Theta wave during Pre-Ictal and Ictal Periods

Table 2 highlights the value of alpha-theta ratios computed from the one minute of EEG data obtained from the simulator. The lowest value in Table 2 is obtained when the continuous sequence of spikes are observed in the ictal waveform.

Table 2: Alpha-Theta Ratios of Ictal EEG

Reading	Alpha-Theta Ratio
1. 0	.3477
2. 0	.3464
3. 0	.4456
4. 0	.5127
5. 0	.6040

As mentioned earlier, a poor neurological outcome is expected when oxygen saturation levels drop below 70%. Recent studies have also shown oxygen desaturation to be correlated with the occurrence of the seizure. Hence, a simple indicator of abnormal oxygen saturation levels would be a drop below 70%. Another indicator of abnormal health conditions would be a very low heart rate. If the heart rate drops to less than 75 percent of his base reading, it is inferred to be abnormal. The metrics for each of sensor readings are summarized in Table 3.

Table 3: Metrics used for each sensor

Property being measured	**Metric Name**	**Normal Value (with respect to baseline readings)**	**Abnormal Value (with respect to baseline reading)**
EEG Critical	EEG	Above 50%	Less than 50%
Oxygen Saturation	Critical Oxygen	Above 70%	Less than 70%
Heart Rate	Critical Heart Rate	Above 75%	Less than 75%

All of the above individual metrics take a value of 1 under abnormal conditions and 0 under normal conditions as outlined in Table 3. These individual metrics can be combined linearly into an overall Criticality Factor, which indicates the level of critical injury suffered by the subjects. The Criticality Factor can be defined as follows:

Criticality Factor = Critical EEG + Critical Oxygen + Critical Heart Rate (1)

Based on this formula, the value of Criticality Factor can assume 4 values from 0 – 3 and the conclusions drawn from each of those values are shown in Table 4. An indicator light, based on the Criticality Factor, is flashed for quick reference. A green LED is flashed to indicate normal conditions, a yellow LED is flashed for a possible abnormality, and a red LED is flashed for critical injury.

Table 4: Inference from value of Criticality Factor

Value for Criticality Factor	**Inference**
0 In	dividual is healthy
1	Abnormality only if Critical Oxygen is one and seizure if Critical EEG is one
2 Possi	ble injury/seizure
3	Seek further medical care

VALIDATION

In this section, we validate the use of the alpha-theta ratio metric we discussed in the previous section for EEG seizure detection. The waveforms plotted in Section 6 and the values for the alpha-theta ration indicated in Table 2 are based on the EEG data obtained from the EEG simulator. While this is actual ictal EEG, values obtained on the basis of a single test may not be conclusive enough to validate the use of the proposed metric for the seizure detection.

Since this study does not involve trials on human subjects, we perform the same processing on actual EEG data, collected from patients suffering from epileptic seizures stored in the EEG database at Albert-Ludwigs Universitat Freiburg, Germany. The database contains invasive EEG recordings of patients suffering from medically intractable focal epilepsy. The datasets are recorded during an invasive pre-surgical epilepsy monitoring. 24 hours of ictal and interictal EEG recordings are carried out. Experienced epileptologists visually inspected the intracranial recordings to determine the ictal periods based on identification of typical seizure patterns preceding clinically manifest seizures. The electrode positions are different for different people. Table 5 shows the values of the alpha-theta ratio calculated during the ictal periods and the value calculated during the inter-ictal period. The value obtained during the inter-ictal period is taken as the baseline value. Since the data is available in digital format, a MATLAB program performing the same processing as the microcontroller is used to obtain the values shown in the Table 5.

As can be seen in Table 5, there is a significant decrease in the alpha-theta ratio in almost all of the readings analyzed. Seizure 2 of the 14 year old patient showed the maximum change with an ictal alpha-theta value o f0.1828 while the baseline value was 0.9296. However in some of the readings a value close to baseline value is seen, although it is smaller than the baseline value. For example, seizure 3 gave a value of 0.76 during the ictal period for the 15 year old female patient, which is close to the baseline value of 0.7804. There could be several reasons for this behavior which cannot be inferred without obtaining additional information about the other conditions of the patients. This validates the use of the metric for seizure onset detection. Figure 9 and Figure 10 show two ictal-seizure patterns that were observed along with the alpha-theta value obtained. The ictal period, similar to the one obtained from the simulator (used in our measurements) shows an increase in the amplitude (or spikes) and a decrease in the alpha- theta value over the baseline values.

Table 5: Alpha Theta values for patients suffering epileptic seizures

Patient Information	Seizure Number	Baseline Alpha-Theta Value	Ictal Alpha-Theta Value
15 year old female	1 0	.7804	0.4575
	2 0	.7804	0.54
	3 0	.7804	0.76
14 year old male	1 0	.9296	0.2560
	2 0	.9296	0.1828
32 year old female	1 1	.3943	0.2786
	2 1	.3943	1.0228
	3 1	.3943	0.9208

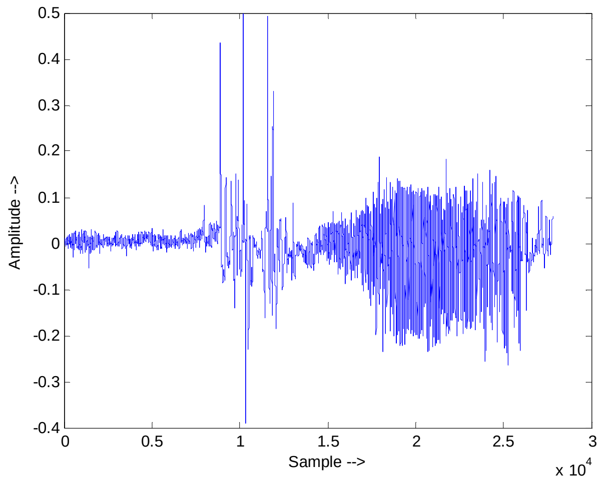


Figure 9: Seizure Pattern 1-Alpha –Theta Ratio = 0.2560

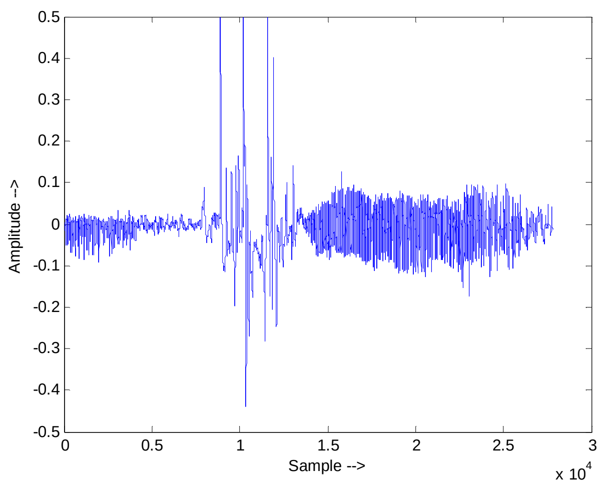


Figure 10: Seizure Pattern 2 -Alpha –Theta Ratio = 0.4575

APPLICATION SCENARIOS

Primary targets for the proposed system are environments where there is a potential risk of brain injury, e.g., the battlefield or high-speed car racing. The light weight and low power requirements make it feasible to embed the device in the protective head gear. For example, in our demonstration of the prototype device we instrument the soldier helmet by embedding the sensors and the processing element into the pads provided within the helmet [24]. Real-time monitoring of a soldier's physiological responses could help gain insight into occurrences of TBI. An earlier study indicated that approximately 10% of the individuals with TBI experience new onset seizures with the risk increasing with increased injury severity. Generalized complex seizures occur in approximately 33% of the cases [25]. Thus, the detection scheme used for detecting TBI could be similar to the one used in our device for identifying seizures. The use of real-time EEG monitoring to detect mild traumatic brain injury by embedding devices in football helmets is proposed in [26].

Another application scenario is continuous patient monitoring where each patient could be connected to a device such as the one proposed in this study. This will allow continuous collecting of relevant data, sending the data to the monitoring base station for logging and further processing. Furthermore, the light weight, the low cost, and the ease of operation make the device usable at a patient's home. In such a scenario, the base station would be smaller equipment with wireless communication capability and flash memory for data storage. An additional facility would be to alert the patient's physician via a Bluetooth module provided in the base station. In case of an emergency, the device could be programmed to send a message using the Bluetooth interface to the patient's mobile phone and then as a text message to the physician. The ability to communicate with the embedded processing equipment wirelessly and alert the physician, as described above, can be integrated seamlessly if a smart mobile phone with Bluetooth connectivity is used as the base station.

The system thus can be adapted to suit the requirements of the application as long as the symptoms being checked for are known and sensors are available for detecting the same.

DISCUSSION

The system presented in this report is capable of real-time collection of physiological data from multiple sensors synchronously and online signal processing to extract relevant metrics in order to make detection decisions. While the results are encouraging, further research is necessary because the analysis in this study was performed on simulated or readily available data. Further research should include extended EEG recordings of several patients. This research would further validate the existing detection system and possibly identify other indicators of abnormalities which would further improve the existing detection system. Additional research would also provide information about why some of the seizure cases analyzed from the EEG database, had ictal EEG alpha-theta ratios that were close to the baseline values.

Metrics

The prospect of coming up with other metrics to make the detection scheme more robust cannot be brushed aside. One important biometric that could prove to be useful in future analysis is coherence.
Coherence, $C_{xy}(f)$ between two waveforms can be defined by the following expression

$$C_{xy}(f) = | P_{xy}(f) | /(P_{xx}(f).\ P_{yy}(f)) \qquad (2)$$

where $P_{xy}(f)$ is the cross-power spectral density of x and y, $P_{xx}(f)$ and $P_{yy}(f)$ are the power spectral densities of x and y respectively. Coherence values range from 0 to 1.
The coherence across the alpha frequency band is used for studies related to cognitive decline. However, it is a complex function to be computed using a microcontroller

during the course of time window while meeting the real-time requirements. This issue is addressed in the discussion on the future work.

Sensor connectivity

An important aspect to take into consideration is the quality of the sensors which are used to collect the measurements. In particular, ensuring uninterrupted connectivity (in particular for the noninvasive sensing such as measurement of EEG and ECG) can be a major problem. For example, there is no easy way to distinguish between a sampled value obtained under normal conditions (i.e., under good connectivity) and values obtained when the sensor is disconnected from the ADC inputs. Another similar case would be maintaining connectivity between the EEG electrodes and the forehead or the pulse oximeter sensor and the skin. Traditional Ag/Cl electrodes can prove to be a problem even if used with a suitable adhesive like an EEG paste. There is considerable focus on developing electrodes which are capable of measuring electrical activity consistently even if there is a minor loss of connectivity between the surface of the skin and the electrode. One such effort would be the use of unique optical voltage sensing technology to measure and monitor electrophysiological parameters. This technique obviates the use of conductive gels to measure EEG signals [21].

Sensor failures

Failure of sensors during operation is a topic which requires attention too. When dealing with analog sensors, it is quite difficult to detect failures unless the condition of operation in failure is significantly different from the normal expected operating conditions. For example, the accelerometers used in our study give a baseline reading of around 1V at rest and depending on the direction of acceleration, the voltage increases or decreases. It may be quite difficult to know when the sensor has actually failed unless the voltage reading consistently stays close to the maximum or minimum observable value. However, this problem can be overcome by using redundant sensors. If the readings from the multiple sensors show a significant difference we know that there is a problem. In order to circumvent this, we can use a majority voting technique with a predefined tolerance value to obtain the actual sensor reading.

Reliable and secure operation

Another important consideration is the reliability and security implications posed by such a device, especially when operated under extreme conditions. Reliability of the device is essential for enabling robust autonomous operation and trustworthy decision making process. A simple hardware based reliability solution would be to introduce redundancy of hardware modules to account for failures or to introduce voting in the decision making stage of the device before making a conclusion about the health status of the individual. For this purpose, a reconfigurable hardware based implementation would provide a suitable platform. With the development of mixed signal FPGA platforms such as Fusion from Actel, future work would focus on development of a reconfigurable embedded system that provides redundant sensors and hardware based signal processing primitives for a fast and reliable processing.

Since communication capabilities are an important part of the device, the question of security is an important one that has to be addressed. Most hardware platforms currently provide for hardware based encryption which is significantly faster and power efficient than its equivalent software counterparts.

The outlined design provides more powerful processing element, which can enable on-line computation of more complex metrics such as the coherence, which is computationally intensive and memory "hungry". Some of the previous studies have used complex processing techniques like wavelet transforms to process EEG waveforms [9]. Wavelet transforms are computation intensive and usually cannot be accomplished using a simple microcontroller. Our future work will focus on exploring novel processing techniques and defining new metrics. Towards this we will explore using FPGA-based platforms for rapid prototyping and testing. The resulting designs can be than implemented as SoC (system on a chip).

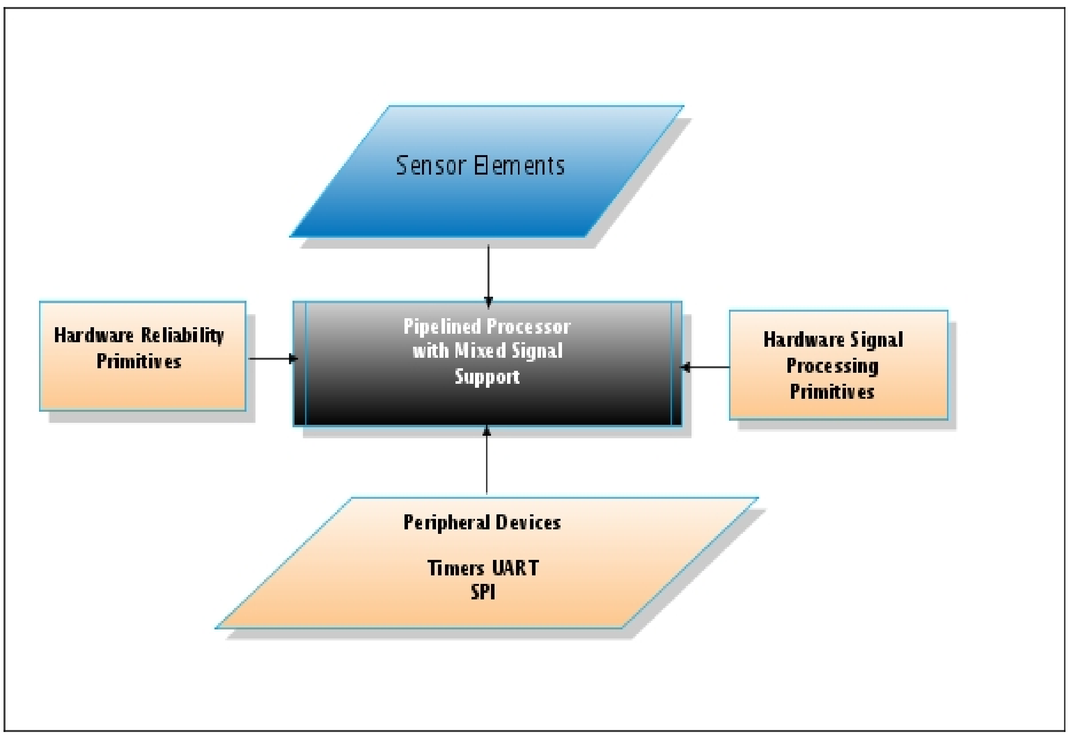


Figure 11: Mixed Signal FPGA Implementation

KEY RESEARCH ACCOMPLISHMENTS

A hardware prototype which is capable of collecting and analyzing data in real-time
Low cost, power efficient
Simple Commercial-Off-The-Shelf components

Non-invasive and cheap sensors
Ability to perform signal processing like digital filtering
Ability to record EEG signals
Ability to record SpO_2 signals
Ability to record accelerometer signals
Ability to send this information wirelessly to a data storage unit

Identification of a metric to indicate the occurrence of a seizure
The alpha-theta ratio shows a significant decrease during the occurrence of a seizure. This observation was validated using the EEG simulator and actual EEG data of patients suffering from epileptic seizures.
Developed a metric which distinguishes between pre-ictal and ictal EEG signals

Ability to embed the hardware prototype inside a combat helmet that is capable of identifying seizures on account of Traumatic Brain Injury.

REPORTABLE OUTCOMES

Papers at Conferences

Ajay M. Cheriyan, Zbigniew Kalbarczyk, Ravishankar K. Iyer, Albert O. Jarvi, Tanya M. Gallagher, Kenneth L. Watkin, Pervasive Embedded Real Time Monitoring of EEG & SpO2 2009 International Workshop on Technologies to Counter Cognitive Decline (TCCD) March 31, 2009 - City University London, UK In conjunction with the 3rd International Conference on Pervasive Computing Technologies for Healthcare (Pervasive Health 09) (accepted for publication), 2009.

Cheriyam, AM, Jarvi, AO, Kalbarczy, Z, Gallagher, TM, Iyer, RK, Watkin, KL, (Pervasive Embedded Systems for Detection of Traumatic Brain Injury, IEEE ICME (accepted for publication), New York, June, 2009.

Cheriyam, AM, Kalbarczyk, Z, Jarvi, AO, Watkin, KL, Iyer, RK, Pervasive Real time Biomedical Monitoring System, IEEE 2nd International Conference on Biomedical and Pharmaceutical Engineering, Singapore, (accepted for publication) , December, 2009

Posters Presentations

Gigascale Research – March 9-10, 2009
CHAD Symposium – March 13, 2009
Engineering Open House – March 13-14, 2009
University of Illinois College of Medicine Research Symposium – April 23, 2009

CONCLUSION

This research shows that creating an embedded system in advanced combat helmet for use in the battlefield is feasible. The final embedded system would be low cost, lightweight and able to record biological signals and process them using a microcontroller. While the system developed in this research is capable processing and distinguishing pre-recorded human EEG signals, the next step would be validate this system using human subjects. By using human subjects, the algorithms used would be improved and the system would be ready for small scale manufacturing and combat condition testing.

REFERENCES

[1] G-Z. Yang, Body Sensor Networks. Springer, 2006.

[2] R. K. Ganti, T. F. Abdelzaher, P. Jayachandran, and J. A. Stankovic, "SATIRE: A Software Architecture for Smart AtTIRE," Proceedings of 4th International Conference on Mobile Systems, Applications, and Services, Mobisys '06, June 2006.

[3] L. M. Hively, N. E. Clapp, V. A. Protopopescu, J. Joseph, C. E. Merican, and T. Lucht, Epileltic Seizure Forewarning by Nonlinear Techniques. Oak Ridge, TN: Oak Ridge National Labs, 2000.

[4] A. Shoeb, S. Schachter, T. Pang, and J. Guttag, "Implementation of closed-loop, EEG-triggered vagus nerve stimulation using patient-specific seizure onset detection from scalp EEG," American Epilepsy Society 61st Annual, Meeting, December 2007.

[5] A. Shoeb, S. Schachter, B. Bourgeois, S.T. Treves, and J Guttag. Impact of Patient-Specificity on Seizure Onset Detection Performance 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, August 2007.

[6] N. Verma, A. Shoeb, J. Guttag, and A. Chandrakasan, "A micro-power EEG acquisition SoC with integrated seizure detection processor for continuous patient monitoring," 2009 Symposium on VLSI Circuits, June 2009.

[7] B. Liu, Y. Zhang, Z. Liu, and C. Yin, "An embedded EEG analyzing system based on uC/os-II," Proceedings of the 29th Annual International Conference of the IEEE EMBS, August 2007.

[8] Y. Mendelson. Wearable Devices for Real-Time physiological monitoring, Dept of biomedical Engineering, Worcester Polytechnic Institute

[9] T. Malina, A. Folkers, and U. G. Hoffman, "Real-time EEG processing based on wavelet transformation," 12th Nordic Baltic Conference on Biomedical Engineering, June 2002.

[10] A. K. Gupta, "Monitoring the injured brain in the intensive care unit," Journal of Postgraduate Medicine, vol. 48, no. 3, pp. 218-225, July-September 2002.

[11] B. Wallace, A. Wagner, E. Wagner, and J. McDeavitt, “A history and review of quantitative electroencephalography in traumatic brain injury,” J Head Trauma Rehabil, vol. 16, no. 2, pp. 165-190, 2001.
[12] K. van der Hiele, A. A. Vein, R. H. A. M. Reijntjes, R. G. J. Westendorp, E. L. E. M. Bollen, M. A. van Buchem, J. G. van Dijk, and H. A. M. Middelkoop, “EEG correlates in the spectrum of cognitive decline,” Clinical Neurophysiology, vol. 118, no. 9, 1931-1939, 2007.
[13] R. Thatcher, D. North, R. Curtin, R. Walker, C. Biver, J. Gomez, and A. Salazar, “An EEG severity index of traumatic brain injury,” J Clinical Neuropsychiatry, vol. 13, no. 1, pp. 77-87, Winter 2001.
[14] S. Ahmad, G. Grindlinger, and S. Desjardins. “Noninvasive cerebral oximetry in patients with traumatic brain injury (TBI),” Critical Care Medicine, vol. 32, no. 12 (Suppl.), p. A104, 2004.
[15] C. M. Dunham, K. Ransom, C. McAuley, B. Gruber, D. Mangalat, and L. Flowers. “Severe brain injury ICU outcomes are associated with cranial-arterial pressure index and noninvasive bispectral index and transcranial oxygen saturation: a prospective, preliminary study,” Critical Care, vol. 10, no. 6, pp. R159-R168, November 2006.
[16] L. M. Bateman, C-S. Li, and M. Seyal, “Ictal hypoxemia in localization related epilepsy: analysis of incidence, severity and risk factors,” Brain, vol. 131, pp. 3239-3245, December 2008.
[17] http://www.cdc.gov/ncpic/factsheets/tbi.htm
[18] T. Zampieri, Testimony, House Committee on Veterans’ Affairs, March 15, 2008.
[19] L. S. Prichep, E. R. John, S. H. Ferris, L. Rausch, Z. Fang, R. Cancro, C. Torossian, and B. Reisberg, “Prediction of longitudinal cognitive decline in normal elderly with subjective complaints using electrophysiological imagin, “Neurobiology of Agin, vol. 27, no. 3, pp. 471-481, March 2006.
[20] E. H. Rubin, M. Storandt., J. P. Miller, D. A. Kinscherf, E. A. Grant, J. C. Morris, and L. Berg, “A prospective study of cognitive function and onset of dementia in cognitively healthy elders,” Arch Neurol, vol. 55, no. 3, pp. 395-401, 1998.
[21] M. Ziejewski, “Selected biomechanical issues of brain injury caused by blasts,” http://www.blastinjuryinstitute.org/biomechanics/Selected+Biomechanical+Issues.
[22] D. L. Trudeau, J. Anderson, L. M. Hansen, D. N. Shagalov, J. Schmoller, S. Nugent, and S. Barton, “Findings of mild traumatic brain injury in combat veterans with PTSD and a history of blast concussion,” J Neuropsychiatry Clin Neurosci, vol. 10, pp. 308-313, 1998.
[23] B. Wahlund, P. Piazza, D. von Rosen, B. Liberg, and H. Liljenstrom, “Seizure (Ictal) – EEG characteristics subgroup depressive disorder in patients receiving ECT – a preliminary study and multivariate approach,” Computational Intelligence and Neuroscience, in press.
[24] A. Cheriyan, A. Jarvi, Z. Kalbarcyzk, R. K. Iyer, and K. L. Watkin, “Pervasive embedded systems for detection of traumatic brain injury,” Proceedings of 2009 IEEE International Conference on Multimedia and Expo, ICME 2009, unpublished.
[25] J. Meythaler and T. Novack, “Post traumatic seizures following head injury,” UAB Traumatic Brain Injury Model System, http://main.uab.edu/tbi/show.asp?durki=10213&site=2988&return=49704, Accessed 9 June 2009.

[26] R. W. Thatcher, "Electroencephalography and mild traumatic brain injury," in Foundations of Sport-Related Brain Injuries, Springer, 2006.
[27] S. A. Kingsley, S. Sriram, A. Pollick, and J. Marsh, "Revolutionary optical sensor for physiological monitoring in the battlefield," Proc. SPIE, vol. 5403, pp. 68-77, 2004.

Award Number: W81XWH-08-1-0208

TITLE: Helmet Integrated Nanosensors, Signal Processing and Wireless Real Time Data Communication for Monitoring Blast Exposure to Battlefield Personnel

PRINCIPAL INVESTIGATOR: Kenneth L Watkin, Ph.D.

Ravishankar Iyer, PhD, Zbigniew Kalbarczyk, PhD, William Sanders, PhD, Janak Patel, PhD

CONTRACTING ORGANIZATION: The University of Illinois at Urbana Champaign
Urbana, Illinois, 61801

List of Workshop & Conference Papers

A.Cheriyan, A. Jarvi, Z. Kalbarczyk, R.K. Iyer, and K.L. Watkin,, “Pervasive Embedded Real Time Monitoring of EEG and SpO_2”
Proceedings of IEEE International Workshop on Technologies to counter Cognitive Decline, TCCD 2009

A. Cheriyan, A. Jarvi, Z. Kalbarczyk, R.K. Iyer, and K.L. Watkin, “Pervasive embedded systems for detection of traumatic brain injury,”
Proceedings of IEEE International Conference on Multimedia and Expo, ICME 2009

A. Cheriyan, A. Jarvi, Z. Kalbarczyk, R.K. Iyer, and K.L. Watkin, “Pervasive Real-Time Biomedical Monitoring”,
To appear in the Proceedings of IEEE International Conference on Biomedical and Pharmaceutical Engineering, ICBPE 2009

Pervasive Embedded Real Time Monitoring of EEG & SpO2

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***Abstract* — Recent research has underscored the potential rol analysis of EEG signals as indicators of cognitive decline. addition, we have also seen the emergence of embedded syste that are capable of analyzing biological signals in real time track a number of physiological variables and make accur conclusions about the individual's physiological status a health. This paper presents the design of an embedded syst which is capable of tracking relevant bio-signals from the per in real time and facilitating a dependable decision mak process that provides alerts for potential brain activity chang The design focuses around the use of sensors and a process element. It incorporates the use of electroencephalography (EI and oxygen saturation (SpO2) signals. As an early proof concept, our system collects data from the sensors, perfoi initial processing and provides the framework to comp significant physiological variables.**

Keywords: cognitive decline, embedded monitoring, EEG and SpO2

I. INTRODUCTION

Recent research on mildly demented AD patients revealed slowing of the EEG, i.e. higher theta power, less beta power and lower peak frequency, were linked to cognitive decline on the cognitive test [1]. Similar results were confirmed by [2] using change in Global Deterioration Scale (GDS) score as an indicator of cognitive decline in subjects with subjective memory complaints. Increases in theta power, slowing of mean frequency and changes in coherence among regions were observed at baseline in subjects who declined after 7-9 years follow-up. Cross-sectional studies in elderly with different levels of cognitive impairment have also reported correlations between EEG spectral parameters, i.e. higher theta activity during rest and lower alpha activity during memory activation and decreased GDS scores [4].

This research on cognitive decline underscores the need for advanced *embedded monitoring systems* that are robust, secure, relatively non-invasive for use in a number environments, e.g. at home, in a residential facility, or hospital. Our vision of such trustworthy, pervasive health technologies is depicted in Figure 1, which shows the conceptual framework and *core architecture*.

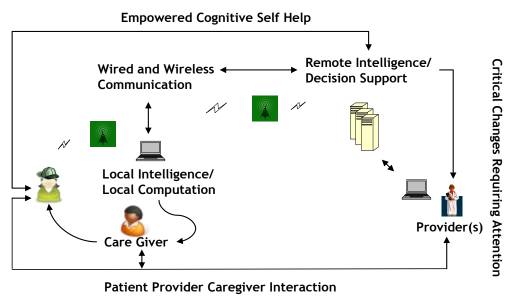

Figure 1: Core Architecture

The above core architecture is intended to represent the key design philosophy of our system, which includes:

- A multi-sensor network consisting of cost-effective wearable sensors, room-mounted sensors, or other types of sensors that gather heterogeneous data.
- Local intelligence where preliminary signal and data processing occur. The local intelligence module can provide immediate feedback to caregivers and patients, and also determine what information to transmit or draw from remote decision-support systems.
- Secure, private, and trustworthy networking capabilities that leverage novel distributed security and privacy algorithms and hardware for low-cost sensors on powerful networks.
- Remote intelligence/decision-support that interfaces to relevant information for decision and control.

The result of applying our core architecture to monitoring and management of cognitive decline are low-cost, highly trustworthy systems that can be easy adapted to the needs of individual users. While in this paper we focus on sensors and systems for detecting symptoms of cognitive decline, the discussed embedded monitoring architecture has the potential for use in a number of environments.

The paper is organized as follows: Section II gives background information. Section III describes the implementation details of the proposed system design. Section IV evaluates and explains the results.

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II. Background

Unlike the painfully obvious losses seen in Alzheimer's disease and other forms of dementia, subtler changes in cognitive functions such as memory, attention, perceptual and motor skills, language and problem solving are common, in the elderly but not universal. In addition, some older adults exhibit "mild cognitive impairment" yet not enough to merit a diagnosis of dementia. Age related cognitive decline usually occurs gradually. Sudden cognitive decline is not a part of normal aging. When people develop an illness such as Alzheimer's disease, mental deterioration usually happens quickly. In contrast, cognitive performance in elderly adults normally remains stable over many years, with only slight declines in short-term memory and reaction times.

Studies of healthy older adults have found a wide range of prevalence of cognitive decline, from less than 10 percent to more than 40 percent of those aged 60 or older, with incidence increasing with age. The broad range may reflect, in part, a lack of consensus about how age-related cognitive decline should be defined, measured and described [3].

Two technologies which have proven effective in monitoring brain activity is pulse oximetry and electroencephalography [4][5]. One downside to both EEG and pulse oximetry is that motion artifacts are common in the signal. There are a variety of methods to remove such artifacts [6][7].

Pulse Oximetry. One benefit of pulse oximetry is that it is noninvasive. Oxygen saturation (SpO_2) can be measured using pulse oximetry. This is important because studies have shown that oxygen saturation is an efficient way to predict neurological outcome in patients with traumatic brain injury. For example, very poor neurological outcome is expected when oxygen saturation is below 70% [8][9]. In normal adults, oxygen saturation remains close to 100%. Another added benefit of most pulse oximetry systems is ability to calculate the heart rate from the same signals used to calculate oxygen saturation levels in the individual. Abnormalities in the heart rate can be monitored and incorporated in the final decision making process, thus eliminating the need for an additional sensor.

Electroencephalogram (EEG). For many years, EEG has been used extensively to monitor brain activity [5]. One difficulty with EEG is that only trained clinicians are able to interpret EEG waveforms. A recent development in EEG technology is quantitative electroencephalography (QEEG). QEEG takes the waveforms and transforms them into bands using a Fast Fourier Transform. This provides a mechanism where decision can be automated. Using QEEG, researchers have shown that some of the important values include theta-alpha ratio, theta relative power, and coherence [1][10].

III. System Design and Implementation

The system design involves the use of sensors to detect various events and produce data which are collected and analyzed by the processing element.

A. Hardware Description

The prototype hardware architecture consists of a set of sensors and corresponding hardware modules for reading, collecting, and processing the sensed data.

a. Oxygen Saturation Module

Oxygen saturation measures the percentage of hemoglobin binding sites in the bloodstream occupied by oxygen. The device used to perform the calculation is called a pulse Oximeter. It relies on the light absorption characteristics of saturation hemoglobin to give an indication of oxygen saturation. The typical method of measurement consists of using a sensor consisting of a source of red and infrared light which is placed in contact with the skin and by computing the ratio of the changing absorbance of light of the two wavelengths, a measure of oxygen saturation can be computed. The OEM III module from Nonin was used for this purpose. The Puresat® Signal Processing technique employed in the module is ideal for use in motion and low perfusion environments. This approach provides more reliable readings over simple microcontroller based pulse oximetry solutions. The sensor is capable of providing a 4-beat average heart rate value and a 4-beat average SpO_2 value.

b. Electroencephalography (EEG) Electrodes

EEG refers to the measurement of the electrical activity produced by the brain. It is recorded using multiple electrodes placed on the scalp. Electrode locations and names are specified by the 'International 10-20' system ensuring consistency in the naming convention. In most clinical applications, 19 recording electrodes along with 2 reference electrodes are used. However, for purposes of this research, only 4 electrodes are used for monitoring abnormal activity. These 4 electrodes are *FP1, FP2, C4* and *O1*. The EEG is typically described in terms of rhythmic activity. This rhythmic activity is divided into bands by frequency. Rhythmic activity with the different frequency changes are known to have a certain biological significance. The different EEG bands are given in Table 1.

Table 1: Different Frequency Bands of EEG Signals

Band	Frequency Range
Delta	1 – 3 Hz
Theta	4 – 7 Hz
Alpha	8 – 12 Hz
Beta	13 – 24 Hz
Gamma	24 – 70 Hz

To develop and test this system we utilized EEG signals generated by an EEG simulator (Grass Techonologies, Model EEGSIM). The same stored signal is replayed with a period of 60 seconds. Several models of the EEG simulator are available with each storing an EEG signal corresponding to different types of EEG waveforms. The simulator that we used for this research simulates the EEG of a person who suffered a seizure.

c. Microcontroller

The information from the sensors is collected and processed by a processor – a microcontroller is used in our design. A microcontroller with sufficient processing power that meets the power constraints of the final design is required. Hence, the MSP430FG4618 from the MSP430 line of microcontrollers from Texas Instruments is chosen. The microcontroller has 116 KB of flash memory and 8 KB of RAM. The important peripherals included in the microcontroller are the Analog to Digital Converter (ADC) and the Serial Communication Interface. It also features support for an LCD segment which can prove to be a valuable peripheral should the need for a text based display arise. A hardware board with this microcontroller is used for the prototype development.

B. System Operation

The sequence of operations carried out by the system ca be explained as follows. First, the signals from the sensors ai collected, namely the oxygen saturation module and EE electrodes. An initial data processing (if required) is carried ou in the pre-processing stage. This is followed by a sequence o operations performed by the microcontroller, the final result o which is the computation and display of the variou physiological metrics. The preprocessed signals are sampled b the ADC integrated within the microcontroller. Th monitoring of sensor signals can be either event triggered o continuous. While the prototype implementation employ continuous monitoring, an event triggered monitoring schem can be easy established with minor software modifications t the microcontroller. In the latter scenario, the trigger to begi monitoring is a software-based detection of an abnormality i the sensed data. For example, an abnormal heart rate or oxyge saturation value (which is anything below/above the baselin value for that person) can be used as a trigger for entering th monitoring mode.

For the EEG electrodes, the preprocessing stage involve amplification and level-shifting. Typical EEG voltages are o the order of micro volts and the simulator generates voltage typically in the range of 5- 50uV with a peak of 500uV. Th voltage is too low to be detected by on-chip ADCs. Hence, th signals are amplified by a factor of 2000 using a hig impedance differential amplifier. EEG signals have a negativ voltage level which is translated to a digital 0. To overcome that, a dc-level shifter is used to add a known DC voltage to the EEG signals before sampling them.

The data values from the oxygen saturation sensor are available in digital format through the serial interface and hence, no pre-processing is required. The frequencies of interest from the EEG signals lie in the 0-70 Hz range. The signals are sampled at a frequency of 500 Hz which is high enough to avoid aliasing. Oversampling can also be done to increase accuracy. Once the signals are sampled, the EEG signals are digitally band-pass filtered to extract rhythmic activity in the different bands as per the classification described in Section III.A. The bands of interest in the detection of cognitive decline are the delta and theta bands. The EEG used here is known to have abnormality on account of seizures. Seizures are known to have spikes in the delta band. Thus, the abnormality in the EEG signal along with oxygen saturation and heart beat information helps us compute a signature or health indicator of cognitive decline.

IV. EVALUATION AND RESULTS

Real-time collection of sensor signals: The system is capable of collecting the signals in real-time in a synchronous manner. Figure 2 depicts the data sampled and collected by the microcontroller. The first four waveforms depict the signals from the four EEG electrodes- *FP1, FP2, C4 and O1-* as analog voltages while the last waveform indicates the oxygen saturation value as a percentage. The samples were collected for a period of 1 minute. The ability to collect the samples synchronously provides the foundation for further processing and shows that an embedded design approach using EEG and other sensors is indeed a feasible approach and a viable

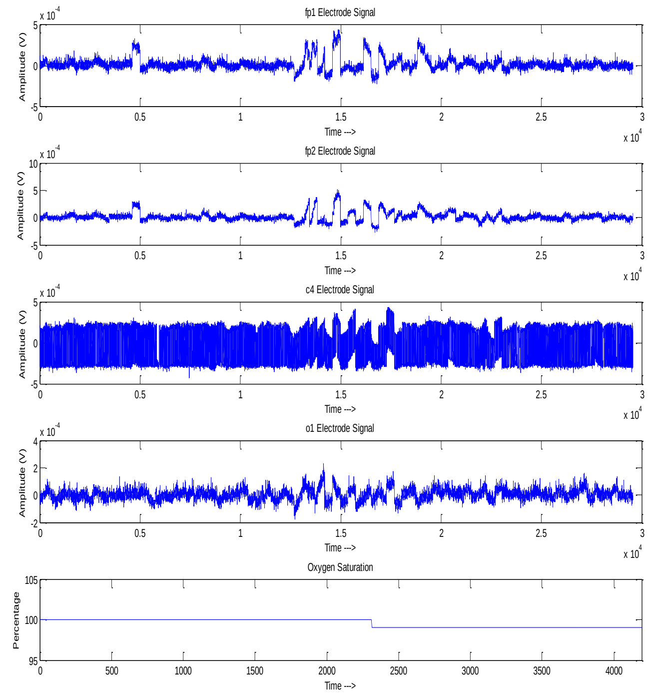

Figure 2: EEG Signals with Oxygen Saturation

Extraction of Frequency Bands: Figure 3 depicts the frequency band information which was extracted from the FP1 EEG electrode. Five (5) different bands are depicted here. The developed system permits the real time extraction of all frequency bands for dynamic analysis of brain activity. It is possible to do the same band information extraction with the signals from other electrodes, but it is not shown here. As mentioned in Section III.B, the EEG simulator generates the signals for a patient who suffered a seizure, which is characterized by spikes in the delta region. The spikes can be seen quite clearly in the first waveform in Figure 3 (see data around sample 15,000) and can be automatically extracted.

Closing the Loop. Different types of real time analyses of the extracted waveforms are possible using the proposed system. For example, the *alpha-theta ratio* of the EEG signals is a typical ratio that is used for biofeedback. It is the ratio of the average power in the alpha band to the average power in the theta band, which can be computed from the area under the power spectral density curve.

Another feedback biometric that can be calculated from the alpha-theta ratio is the *theta-relative power* which is the ratio of average power in the theta band to the total power in alpha and theta bands. Yet, another important analysis of EEG bands is the analysis of the functional connectivity between hemispheres and within hemispheres – *coherence*. Coherence, $C_{xy}(f)$, between two waveforms can be defined as the following expression:

$$C_{xy}(f) = |P_{xy}(f)|^2 / P_{xx}(f) P_{yy}(f) \qquad (1)$$

Where, $P_{xy}(f)$ is the cross-power spectral density of x and y; $P_{xx}(f)$ and $P_{yy}(f)$ are the power spectral densities of x and y, respectively. Coherence values range from 0 to 1. As an example, the coherence was calculated for the alpha frequency band in the FP1 and FP2 electrodes. The coherence across the alpha band is generally used for studies pertaining to cognitive decline though it can be computed for the other bands as well. Table 2 lists the alpha-theta ratio, theta relative power and coherence values calculated across the alpha bands for some of the electrode signals. For example, the computed alpha-coherence for FP1 and FP2 is only 0.181, which indicates weak correlation between the alpha waves collected from the two electrodes. This may be due to significant difference in the activity in the left and right site of the brain. The purpose of showing these results is to demonstrate that the proposed system, while relatively simple, is powerful enough to collect real-time data and compute on-line metrics, which can be used as health indicators, e.g., cognitive decline of the subjects.

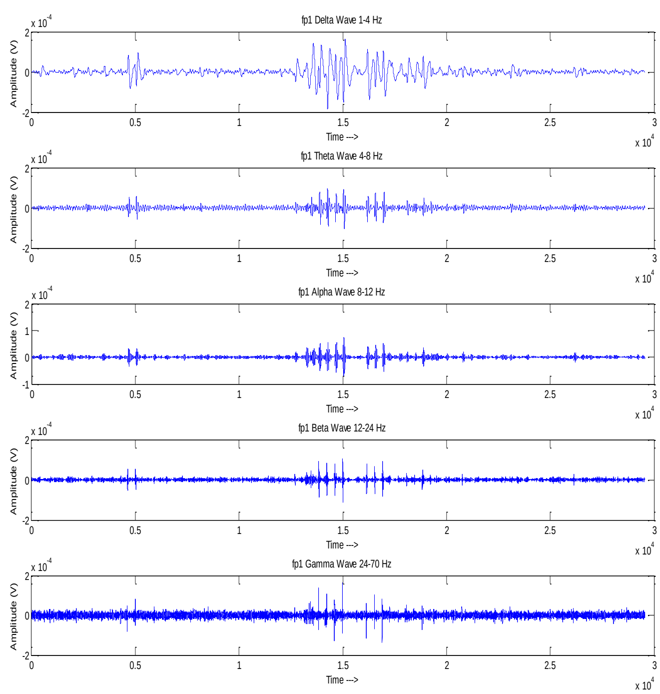

Figure 3: Delta, Theta, Alpha, Beta and Gamma Bands of FP1 Electrode

Table 2: Values of Computed Metrics

Metric	Value
Alpha-Theta Ratio for FP1	0.393
Alpha-Theta Ratio for FP2	0.40
Theta Relative Power for FP1	0.7179
Theta Relative Power for FP2	0.7094
Alpha-Coherence for FP1, FP2	0.181
Theta-Coherence for FP1, FP2	0.768

V. CONCLUSIONS AND FUTURE WORK

In this paper, we present an embedded system framework that is capable of collecting and analyzing data from sensors to calculate suitable metrics from which we can infer the physiological status of a person. Future work will focus on: (i) adding more sensors to monitor other human body responses, (ii) maintaining redundant sensors to account for reliable operation of the module, (iii) developing robust algorithms for analyzing various types of brain injuries, and (iv) adding support for the other features envisioned in the core architecture, e.g., wireless communication in a secure and trustworthy manner.

REFERENCES

[1] K. van der Hiele, A. A.Vein, R. H. A. M. Reijntjes, R. G. J. Westendorp, E. L. E. M. Bollen, M. A. van Buchem, J. G. van Dijk, and H. A. M. Middelkoop, "EEG correlates in the spectrum of cognitive decline," Clin Neurophysiol, vol. 118, no. 9, pp. 1931-1939, 2007.

[2] L. S. Prichep, E. R. John, S. H. Ferris, L. Rausch, Z. Fang, R. Cancro, C. Torossian, and B. Reisberg, "Prediction of longitudinal cognitive decline in normal elderly with subjective complaints using electrophysiological imaging," Neurobiology of Aging, vol. 27, no. 3, pp. 471-481, March 2006.

[3] Rubin EH, Storandt M, Miller JP, et al. A prospective study of cognitive function and onset of dementia in cognitively healthy elders. *Arch Neurol* 1998;55(3):395–401.

[4] A. K. Gupta, "Monitoring the Injured Brain in the Intensive Care Unit," Journal of Postgraduate Medicine, vol. 48, no. 3, pp. 218-225, July-September 2002.

[5] B. Wallace, A. Wagner, E. Wagner, and J. McDeavitt, "A history and review of quantitative electroencephalography in traumatic brain injury," J Head Trauma Rehabil, vol. 16, no. 2, pp. 165-190, 2001.

[6] M. Petterson, V. Begnoche, and J. Graybeal, "The effect of motion on pulse oximetry and its clinical significance," Anesthesia and Analgesia, vol. 105, no. 6, pp. S78-S84, December 2007.

[7] S. Bailey, E. Hall, S. Folger, and P. Miller, "Changes in EEG during graded exercise on a recumbent cycle ergometer," Journal of Sports Science and Medicine, vol. 7, pp. 505-511, Dec 2008.

[8] S. Ahmad, G. Grindlinger, and S. Desjardins, "Noninvasive cerebral oximetry in patients with traumatic brain injury (TBI)," Critical Care Medicine, vol. 32, no. 12 (Suppl.), p. A104, 2004.

[9] C. M. Dunham, K. Ransom, C. McAuley, B. Gruber, D. Mangalat, and L. Flowers, "Severe brain injury ICU outcomes are associated with cranial-arterial pressure index and noninvasive bispectral index and transcranial oxygen saturation: a prospective, preliminary study," Critical Care, vol. 10, no. 6, pp. R159-R168, November 2006.

[10] R. Thatcher, D. North, R. Curtin, R. Walker, C. Biver, J. Gomez, and A. Salazar, "An EEG severity index of traumatic brain injury," J Neuropsychiatry Clin Neurosci, vol. 13, no. 1, pp. 77-87, Winter 2001

PERVASIVE EMBEDDED SYSTEMS FOR DETECTION OF TRAUMATIC BRAIN INJURY

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ABSTRACT

Transient explosions on the battlefield result in blast injuries that are polytrauma in nature. That is, along with physical wounds additional injury can include cognitive and communication impairments related to traumatic brain injury (TBI). The design of a multisensor system embedded in an advanced combat helmet is presented that is capable of real time tracking of physiological signals (EEG, blast pressure, head acceleration, oxygen saturation and heart rate) and facilitating a reliable and dependable decision making process that provide alerts for potential traumatic brain injury. The cyperphysical system focuses on the use of heterogeneous sensors within the helmet pads and a processing element for real time algorithmic processing.

***Index Terms* —** traumatic brain injury, bio-sensing, EEG and SpO2 ,embedded monitoring

1. INTRODUCTION

Traumatic Brain Injury (TBI) is a complex injury with a broad spectrum of symptoms and disabilities, the impact of which on a person can be profound and devastating. TBI may be missed during the early stages of diagnosis when the focus is on critical injuries or ones with visible symptoms. If TBI is associated with loss of consciousness and confusion for less than 30 minutes, it is generally classified as mild and if it lasts for more than 30 minutes and is associated with memory loss, it is categorized as severe. According to the United States Center for Disease Control and Prevention, there are approximately 1.5 million people in the US who suffer from TBI each year [1]. Early diagnosis of TBI can go a long way in significantly reducing the impact of the injury.

TBI is caused by open head injuries which include bullet wounds, closed head injuries which result from falls, motor vehicle crashes, chemicals, deceleration injuries or hypoxia (lack of oxygen). The two causes which are of importance in this paper are deceleration injuries and hypoxia. Deceleration injury refers to the rapid movement of the skull through space followed by immediate deceleration which causes the brain to move inside the skull. Different parts of the brain move at different speeds because of their relative lightness or heaviness. When the brain is slammed back and forth inside the skull, it is alternately compressed and stretched because of its gelatinous consistency. If the impact is strong enough, axons can be stretched until they are torn. This is called axonal shearing and the neuron dies. After a severe TBI, there is massive axonal shearing. The other cause that is of significance is hypoxia or lack of oxygen. This condition may be caused by heart attacks, drops in blood pressure and being present in a low oxygen environment. This type of TBI can cause severe cognitive and memory defects.

In this paper we present the research and development of a reliable, fault- tolerant embedded monitoring system for the real time identification of traumatic brain injury of soldiers in the battlefield exposed to blast pressures. The rest of the paper is organized as follows: Section II provides background information and explains previous work in this area; Section III gives an overview of the system design, Section IV describes some initial results and Section V discusses the impact of the project and future work.

2. BACKGROUND

Transient explosions on the battlefield result in blast injuries that are polytrauma in nature. That is, along with physical wounds addition injury can include cognitive and communication impairments related to TBI (traumatic brain injury), swallowing impairments, aphasia, motor speech impairment, medical conditions requiring trach and vent, and hearing loss. As of March 8, 2007 23,417 traumatic combat injuries have been reported [2]. 11,852, approximately 51%, returning wounded had been exposed to blast injuries, the most common being from Improvised Explosive Devices (IEDs).

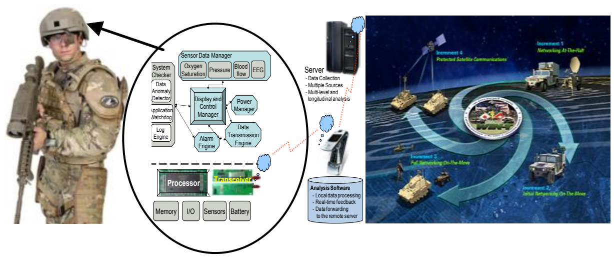
In addition, military personnel are surviving beyond the acute phase of blast injuries due to improvements in body armor, battle-site and acute trauma care. They are surviving with new, multiple and complex patterns of injuries including traumatic brain injury, traumatic limb amputation, nerve damage, burns, wounds, fractures, vestibular damage, vision and hearing loss, chronic pain, mental health, and adjustment.

TBI poses the great risk because it may be caused by all four mechanisms (primary, secondary, tertiary and quaternary) of blast injury. Blast over-pressurization exposure adds significant complexity to the profile of blast cases with TBI. First responders and medical teams need to have information on the level of blast exposure to the brain as well as critical data regarding the physiological functioning of cortical systems. Recording blast events and physiological responses using smart nanotechnology embedded into helmet supporting structures would provide vital information for first responders and forward medical teams. The utilization of a combination of sensor inputs designed to monitor brain function, pre and post blast exposure, may provide (i) insights into prediction of recovery from battlefield blast exposure and traumatic brain injury and (ii) information for in-depth clinical diagnostics and rehabilitation in a polytrauma rehabilitation center and for in the home long term care for individuals with TBI/PTSD (Post Traumatic Stress Syndrome). These new bio-sensing monitoring technologies help build a continuum of care for military personnel and as an in-field device form a platform of epidemiological data gathering on TBI occurrence (see Figure 1).

Figure 1: Pervasive Monitoring Systems for TBI/PTSD - A Continuum of Care

Research has indicated that level of blast pressure, head acceleration and electroencephalographic (EEG) waveform changes are significant indicators of potential traumatic brain injury [3][4].

The continued exposure to potentially concussive forces due to the blast pressure created by improvised explosive devices has motivated our development of a multiple set of physical and physiological recording sensors embedded in the pads of the Advanced Combat Helmet (ACH). These sensors are securely connected to a small processing device within the helmet. The fundamental task for this embedded monitoring system is to provide alerts signaling changes in cognitive activity to the individual soldier as well as pervasively to functional groups of soldiers and medical/material command. See Figure 2.



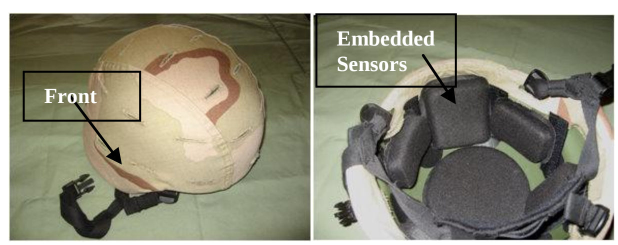
(a) (b)

Figure 2: Embedded System Schematic a) Soldier Level, b) Pervasive Level

3. SYSTEM DESIGN AND OPERATION

The developed prototype enables direct helmet based recording and execution of reliable algorithms that record blast pressure, frontal qEEG, SpO2 and head acceleration. The sensed data indicates the potential presence of trauma brain injury while simultaneously providing vital sign information profiles. Integrating magnitude of blast with predictive algorithms regarding the level of blast injury provides early warnings of soldier status. Gathered information can be available immediately to first responders using a cell-phone-like handheld device that will also be used to port the information directly to medical staff, military medical databases, military hospitals and polytrauma rehabilitation centers.

Presented in Figure 3 are the locations of our sensors embedded within the pads of the ACH to record blast pressure, head acceleration and rotation, frontal EEG, SpO2 and heart rate.



(a) (b)

Figure 3: Helmet with embedded sensors

The location of the sensors is determined in part by the geometry of the helmet in the case of the accelerometer for blast pressure monitoring. The SpO2 sensors and the EEG electrodes are placed in the front pad for two principle reasons- the forehead provides a clear recording area and validation of SpO2 from the forehead is well documented and is routinely employed in clinical settings. The first prototype includes frontal EEG electrodes. This location is chosen for accessibility reasons and it is well known that the frontal lobe is involved significantly in TBI. Also, analyzing frequency, power spectrum, coherence, amplitude and phase characteristics of the theta, delta and gamma components may provide strong indices of altered brain activity [1]. The primary purpose of the ACH is to provide an alerting signal that medical personnel need to examine the soldier. The system is not intended for diagnosing specific locations of brain injury.

The recording strategy for this new, advanced ACH has two components, 1) automatic all channel ***baseline*** monitoring/storage of EEG, SpO2 and heart rate once the helmet is donned and 2) real time monitoring blast pressure, EEG, SpO2, heart rate, head surface acceleration and head rotation triggered by the blast pressure. For example, in the battlefield the blast pressure accelerometer is always on in low power 25 μsec monitoring mode. Once the blast pressure rises above the preset threshold all channels are instantly recording head acceleration and rotation values in real time along with the physiological variables - EEG, SpO2, heart rate for three continuous minutes. Recorded variables are then analyzed for level of brain injury and data. Resulting algorithmic process provides three levels of alert - red (potentially moderate brain injury), yellow (mild brain injury), and green (no apparent injury). These ratings are wirelessly forwarded to in-unit battlefield personnel and to emergency field personnel. An in-helmet low power LCD alert is also provided. Coordination of data acquisition and processing along with wireless communications along with data distillation algorithms is currently accomplished using the Texas Instruments MSP430 microprocessor platform that is an ultra-low-power 16-bit RISC mixed-signal processor embedded into the inside side wall of the helmet. Displayed in Figure 4 is the prototyping board for the system. The processor and associated algorithms also provide for color coded in-helmet alerts as well as wireless alerts to accompanying personnel and medical teams.

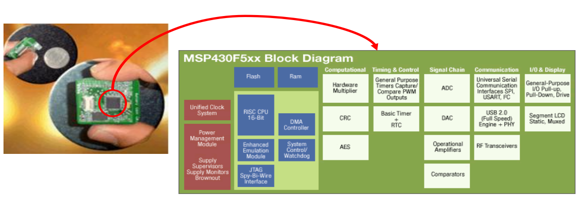


Figure 4: Prototyping Board with the MSP430 Microcontroller

4. EVALUATION AND RESULTS

The blast pressure accelerometer (high g force rating) is hermitically sealed to the side wall of the ACH, under the camouflage, and is connected to the microcontroller with sealed wiring. This sensor has a low power requirement and provides real time magnitude of blast pressures and also triggers data acquisition from the biosensor group (acceleration, EEG, oximetry, & heart rate). Additional accelerometers embedded within the ACH pads provide real time data on head rotation as well as acceleration at the head surface. All of our tests on the helmet to date are based on simulated data to the helmet monitoring devices (CDMRP Concept Awards* did not permit the use of human subjects). Along with current testing using simulated real EEG signal (Grass Technologies, Model EEGSIM), a Nonin OEM III small footprint (24.1mm x 34.5mm), low power draw pulsed oximetry device was used to monitor oxygen saturation.

Figure 5 shows the real-time data collected by the proposed system from the sensors. The first three signals indicate the acceleration along the three axes of the accelerometer, the fourth indicates the oxygen saturation level and the final four signals indicate the voltages observed on EEG electrodes FP1, FP2, C4 and O1. These names are as per the 'International 10-20' naming standard for EEG electrode locations. The spikes or peaks observed in the accelerometer voltages indicate blast pressure which is a voltage considerably above the baseline level. Although acceleration is displayed as a vector quantity here, the scalar magnitude is used to determine the occurrence of a blast. Oxygen saturation is displayed as a percentage and in a healthy adult, arterial blood is almost a 100 percent saturated. The EEG simulator used for testing has the EEG signal of a person suffering a seizure. An indicator for seizure is the presence of spikes in the EEG waves which can be seen around the 15000 sample mark in the FP1 and FP2 waveforms. Since human subjects were not included in the study, a normalized TBI indicator metric is computed based on the existence of spikes in the EEG waveform and a low oxygen saturation value (less than 70%) after a blast pressure is detected. This value is then displayed on a visual indicator like an LCD or using LEDs as power consumption is a constraint for embedded devices. In the next generation of the prototype, small IR (infrared) sensors and the associated on board algorithms that eliminate motion artifact will be integrated into our system to compute real time output of SpO2 and simultaneous heart rate value.

5. FUTURE WORK

The creation of a cyberphysical system that permits real time human physical and physiological tracking has enormous impact for health and healthcare. The system developed for this application can be easily transported for use as diagnostic and/or rehabilitation tool as well as for augmentative purposes for various complex tasks.

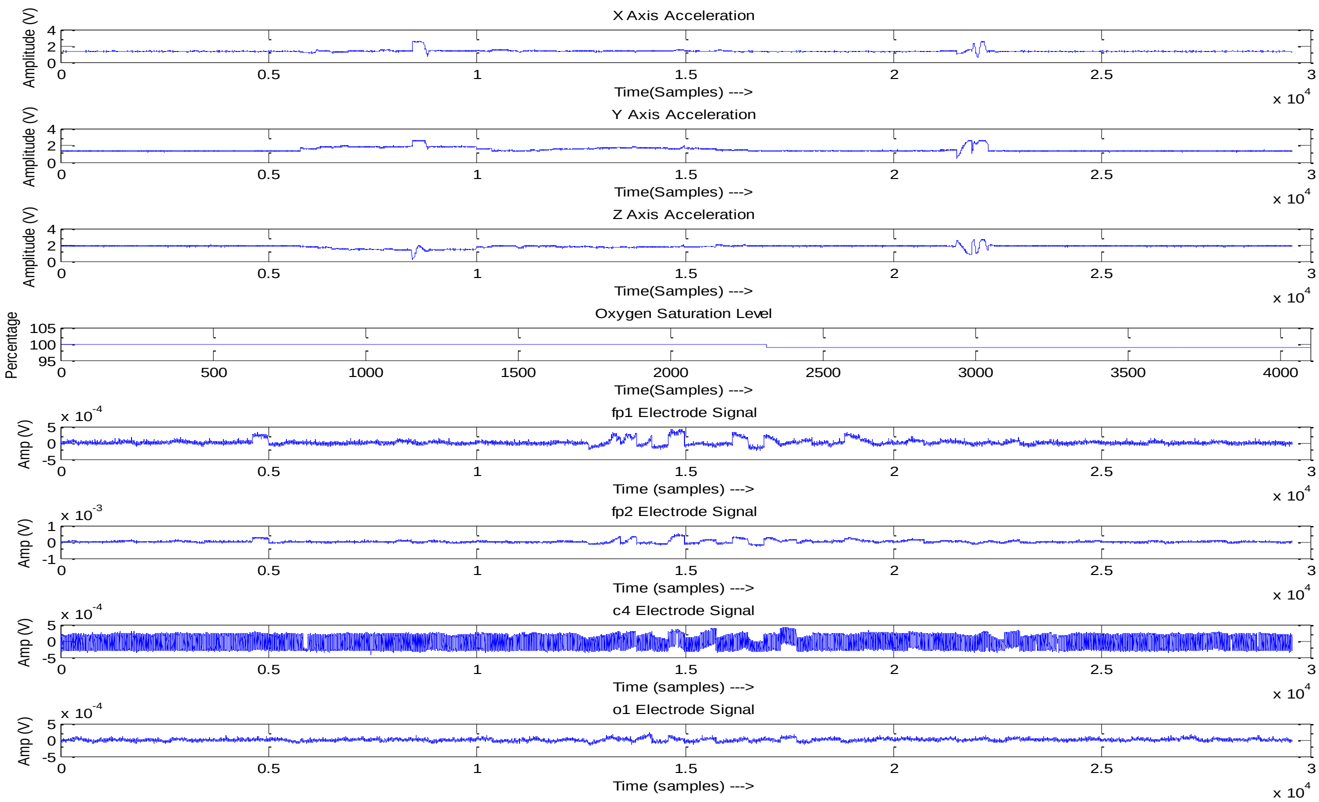


Figure 5: Synchronous Collection of Accelerometer, EEG and SpO2 Signals

REFERENCES

[1] http://www.cdc.gov/ncpic/factsheets/tbi.htm

[2] Zampieri T, Testimony, House Committee on Veterans' Affairs, March 15, 2008

[3] Ziejewski, M, Selected Biomechanical Issues of Brain Injury Caused by Blasts, http://www.blastinjuryinstitute.org/biomechanics/Selected+Biomechanical+Issues

[4] Trudeau, David L., Anderson, John, Hansen, Lisa M., Shagalov, Diana N., Schmoller, Joseph, Nugent, Sean, Barton, Stephen Findings of Mild Traumatic Brain Injury in Combat Veterans With PTSD and a History of Blast Concussion J Neuropsychiatry Clin Neurosci 1998 10: 308-313

[5] A. K. Gupta, "Monitoring the Injured Brain in the Intensive Care Unit," Journal of Postgraduate Medicine, vol. 48, no. 3, pp. 218-225, July-September 2002.

[6] B. Wallace, A. Wagner, E. Wagner, and J. McDeavitt, "A history and review of quantitative electroencephalography in traumatic brain injury," J Head Trauma Rehabil, vol. 16, no. 2, pp. 165-190, 2001.

[7] M. Petterson, V. Begnoche, and J. Graybeal, "The effect of motion on pulse oximetry and its clinical significance," Anesthesia and Analgesia, vol. 105, no. 6, pp. S78-S84, December 2007.

[8] S. Ahmad, G. Grindlinger, and S. Desjardins, "Noninvasive cerebral oximetry in patients with traumatic brain injury (TBI)," Critical Care Medicine, vol. 32, no. 12 (Suppl.), p. A104, 2004.

[9] Roche, R, Dockree, P, Garavan, H, Foxe, J, Robertson, I, O'Mara, S, EEG alpha power changes reflect response inhibition deficits after traumatic brain injury (TBI) in humans, Neuroscience Letters, 362,(13): 1-5, 2004.

[10] R. Thatcher, D. North, R. Curtin, R. Walker, C. Biver, J. Gomez, and A. Salazar, "An EEG severity index of traumatic brain injury," J Neuropsychiatry Clin Neurosci, vol. 13, no. 1, pp. 77-87, Winter 2001.

Pervasive Real-Time Biomedical Monitoring System

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Abstract – **With the tremendous advancements in low cost, power efficient hardware and the recent interest in biomedical embedded systems, numerous traditional biomedical systems can be replaced with smaller embedded systems that do real-time analysis to provide bio-feedback to the users. This paper presents a prototype of an embedded system which is capable of real-time data collection, using analog and digital sensors and processing, to compute physiological variables and metrics. These metrics in turn can be used to determine information about the user's general well being. The sensors provide motion, brain wave activity (EEG) and blood oxygenation (SpO_2) information. The system presented automatically computes the application specific metrics and indicates the results of the detection scheme to the user and to a monitoring base station. The metrics being used have been validated using raw data from patients suffering epileptic seizures and from past research. The paper also deals with application scenarios for such systems and architecture for an FPGA based implementation is discussed.**

Keywords: - Health monitoring, embedded systems, EEG, SpO_2, configurable hardware

I. INTRODUCTION

Over the past two decades, the hardware industry has followed Moore's law resulting in faster processors using smaller and more power efficient transistors. This shrinkage of size and increase in processing power has caused an explosion in the number of embedded systems for various applications with the most prominent among them being mobile phones. However, devices used in the medical field require significant processing capabilities because of the vast amount of data processing involved in acquiring physiological signals. It is only recently that it has become feasible to utilize this increased processing power for embedded and cyberphysical systems supporting biomedical applications. Cyberphysical systems differ from traditional embedded systems in the fact that there are a number of processing elements and sensors which coordinate amongst themselves to accomplish a task. In cyberphysical systems, the emphasis tends to be on the interaction between the computational and physical elements.

One of the relevant studies in this field focuses on providing Body Sensor Networks by utilizing modified wireless sensor network platforms for biomedical applications [1]. The hardware platforms consist of a processing element with integrated sensors (e.g., temperature sensors, accelerometers) and a wireless transceiver. Such sensor networks are employed to monitor patient activities, record the relevant information, and initiate actions based on the information collected. An example of such a system is the SMART Attire or SATIRE which provides wearable computing to monitor activities of a person [2].

While such systems deal with non-critical data collected from the human subjects, a more difficult challenge arises when collecting accurate physiological data, which is essential for correct diagnosis and to initiate appropriate feedback action. Thus, ensuring reliable data processing and automated decision making is extremely important to trust the conclusions drawn from the data.

In this paper, we present an embedded system that is capable of collecting data from physiological sensors (e.g., EEG, oxygen saturation, and accelerometers) in a synchronous manner and analyzing the data in real time to detect abnormalities in the waveforms and warn the user in the due time. The contributions of the paper include:

1. The architecture of a low cost, power efficient biomedical embedded monitoring and diagnostic device that is capable of collecting and analyzing data in real time.
2. The implementation and evaluation of a prototype device based on the above architecture designed to detect conditions such as traumatic brain injury (TBI), seizures, and cognitive decline.

The rest of the paper is organized in the following manner. Sections 2 and 3 present related work and background information. Sections 4 and 5 describe the architecture and the prototype, Sections 6 and 7 evaluate and validate the principles of the detection scheme implemented in the device. Section 8 describes application scenarios followed by a discussion on the implementation issues and future work in Section 9.

II. RELATED WORK

Prerecorded human EEG recordings, which were free of artifacts, were used in this research to provide a foundation for evaluating the performance of the developed system prior to human subject use. Since most of the EEG data available pertain to seizures, we discuss the work related to detection and analysis of seizures.

Hively et al. under the CRADA hardware and software setup utilizes non-linear techniques in EEG forewarning equipment [3]. This method works by using a three dimensional phase space representation of the collected data. Seizure occurrence is predicted from the dissimilarities between the distribution function for the non-seizure waveforms and seizure waveforms. However, this device is exclusively limited to detecting seizures. Environmental conditions under which the patient is operating are not taken into account. This considerably limits the application space of the device. Verma and colleagues focus on small footprint SoC solutions for continuous patient EEG monitoring and seizure prediction devices [4] [5] [6].

Considerable work has been done in the area of embedded devices for collecting EEG data with reduced artifacts [7] [8]. Such devices or solutions focus only on the data collection aspect of the EEG data with almost no processing carried out in real-time. Reference [9] below describes a real-time EEG processing device based on TI's signal processing platform which decomposes the collected EEG data into various frequency bands for visualization purposes. However, the power consumption of such a device can be quite high limiting its use in a power constrained embedded environment.

The system prototype described in this paper differs from the systems described above in the ability to collect EEG, oxygen saturation, and heart rate data in real time and detect abnormalities in the data before alerting the user and a remote logging base station. The device uses a standard Commercial Off the Shelf (COTS) power-efficient device (e.g. microcontroller) to realize this goal in addition to several inexpensive and non-invasive sensors. The cost-effectiveness and adaptability to several application scenarios make our solution quite unique.

III. BACKGROUND

Monitoring brain activity has been useful in detecting and explaining brain injuries and disorders in individuals. Two commonly used technologies for this purpose are pulse oximetry and electroencephalography [10] [11].

Electroencephalogram (EEG): For many years, EEG has been used extensively to monitor brain activity. One difficulty with EEG is that only trained clinicians are able to interpret EEG waveforms and identify abnormalities. Quite recently, however studies have focused on utilizing digitized EEG data to extract useful information. This is called Quantitative EEG (QEEG). QEEG helps to transform the waveforms into frequency bands using Fast Fourier Transform or other filtering techniques. Once a pattern in such a scheme is associated with an abnormality, there exists a mechanism for automated decision making. Using QEEG, researchers have shown that some of the important values are alpha-theta ratio, theta-relative power and coherence [12][13]. Alpha-Theta ratio is explained in Section 6 and Coherence is explained in Section 9.

Pulse Oximetry: Oxygen saturation (SpO_2) can be measured using pulse oximetry. One benefit of pulse oximetry is that it is non-invasive. Studies have shown that oxygen saturation is an efficient indicator of neurological outcome in patients with traumatic brain injury. In normal adults, oxygen saturation remains close to 100%. Cognitive ability and normal brain functions begin to be affected when oxygen saturation is below 90%. Very poor neurological outcome is expected when oxygen saturation is below 70% [14] [15]. In some patients with epileptic seizures, oxygen saturation levels have been shown to drop below 90%, while some drop below 70%, soon after seizure onset [16].

IV. SYSTEM DESCRIPTION

In this section, the various modules involved in the prototype system are discussed.

Accelerometers. Accelerometers help capture the acceleration of an object in terms of an analog voltage which is directly proportional to the dynamic acceleration experienced by an object. In other words, a device at rest will indicate a value of acceleration equal to $9.8m/s^2$ or 1g along the vertical axis. However, in most cases, the value of acceleration would be non-zero along the other axes, which makes it necessary to calculate the baseline values of acceleration for a body at rest. The accelerometers are part of this design for its use in applications where the risk of injury is related with an action that results in quick movement of the person or object. (One such scenario is described in Section 8.) The accelerometers used in this system are MEMSIC's heat transfer based micrometer sized devices which offered significantly improved performance over traditional proof mass based systems and have a shock rating of over 50,000g. The prototype used models of the device with a higher sensitivity, 500mV/g and range of +/-1.7g at 3V. This is to obtain a measurable voltage with reasonable movement under the lab's testing conditions. Accelerometers with lower sensitivity can be used when the total acceleration to be expected is higher. Tri-axial accelerometers are used in this prototype.

Oxygen Saturation and Heart Rate Monitor. Oxygen saturation measures the percentage of hemoglobin binding sites in the bloodstream occupied by oxygen. The device used to perform the calculation is called a pulse oximeter. It relies on the light absorption characteristics of saturated hemoglobin to determine the percentage of oxygen contained. The typical method of measurement consists of using a sensor containing red and an infra-red or near infra-red light emitting diodes. The diodes are placed in contact with the skin along with photodiodes to determine the amount of light from the two sources which are absorbed and reflected. This data is used to compute the oxygen saturation.. As mentioned earlier, oxygen saturation under normal conditions is close to a 100%.

The wave patterns, picked up by the photodiodes, display an *ac* value with a *dc* component. As can be intuitively understood, since we are computing the blood oxygen saturation levels, the frequency of the *ac* component gives us the heart rate of the individual. Hence, most pulse oximeters are capable of computing the heart rate. Due to the availability of commercial devices which are capable of computing these values accurately with minimal artifacts, a commercial product was used for our purpose. The OEM III module from NONIN is used in this study.

The Puresat Signal® processing technique employed in the module is ideal for use in motion and low perfusion environments. This approach provides more reliable readings over simple microcontroller based pulse oximetry solutions. The NONIN sensor provides a 4 beat average heart rate and a 4 beat average SpO_2 values.

EEG Electrodes. EEG refers to the measurement of the electrical activity of the brain and is recorded by placing multiple electrodes on the scalp. Electrode locations and names are specified by the International '10-20' system ensuring consistency in the naming convention. In most clinical applications, 19 electrodes along with two reference electrodes are used. Most of the EEG data used in this study is obtained from patients suffering from seizures. With regard to seizures, an important term is the *Ictal* period. *Ictal* period is the duration of the actual seizure and the EEG reading during this period is the ictal EEG. The time shortly before and after the seizure are called *Pre-Ictal* and *Post-Ictal* respectively. The time between two seizures is the *Inter-Ictal* period and for epileptic patients, most of the EEG readings correspond to this period.

A significant amount of seizure activity is observed in the frontal region of the brain (i.e. in the electrodes placed on the forehead) and hence, most of the study and detection schemes used in this research focus on Fp1 and Fp2 electrodes. The waveforms observed on the two electrodes are quite similar. This can be expected because of the symmetrical placing of the two electrodes on the forehead. Hence for our analysis, we focus on the signal from the Fp1 electrode. One recent study on EEG characteristics related to depressive disorder conducted with data collected during the ictal period of the seizure observed maximum change on the Fp1 electrode [17].

As mentioned previously, rhythmic activity within the different bands of the EEG frequency spectrum are known to have biological significances and this is utilized in the detection scheme. The different EEG bands are outlined in Table 1.

Table 1: Different Frequency Bands of EEG Signals

Band	Frequency Range
Delta	1 – 3 Hz
Theta	4 – 7 Hz
Alpha	8 – 12 Hz
Beta	13 – 23 Hz
Gamma	24 – 70 Hz

To develop and test the prototype, we utilize EEG signals generated by an EEG simulator (Grass Technologies, Model EEGSIM). The simulator has a patient's ictal EEG stored on a PROM (Programmable Read Only Memory) which is replayed every 60 seconds. Several models of the EEG simulator corresponding to different types of EEG waveforms are available.

Microcontroller. The central processing element of the device is a microcontroller which is capable of collecting the data from the different sensors and processing them. In addition to the processing power, limiting the power consumption was an important constraint. The MSP430FG4618 from the MSP430 line of microcontrollers was chosen for this purpose. The microcontroller has 116KB of flash memory and 8 KB of RAM. The important peripherals included in the microcontroller are the Analog to Digital Converter, the Serial Communication Interface and the Serial Peripheral Interface. It also features the support for an LCD module, which can be used to provide visual feedback to the user should the application demand it. A development board with the microcontroller was used for the prototype development.

Wireless interface. The device has been designed keeping in mind the desire to communicate the results of the monitoring procedure to a base station which is capable of logging the results periodically or to communicate the result to another piece of equipment. For this purpose, a wireless communication interface was also setup. The Chipcon CC2500 module from Texas Instruments is used for this purpose. It is a low power and low cost transceiver used for wireless communication in the 2.4GHz ISM band based on the ZigBee protocol. It is capable of transmitting in packets of 64 bytes along with support for a low power sleep mode operation.

V. SYSTEM OPERATION

In this section, the operation of the device is explained. The signals from the sensors, namely the accelerometers, pulse oximetry module, and EEG electrodes are first processed the analog to digital converter (ADC) before being collected by the microcontroller. The signals from the accelerometers can be low pass filtered if desired, but the dc component of the waveform should not be eliminated to obtain a higher analog voltage of acceleration. Low analog voltages can suffer attenuation resulting in faulty decision making. Two dual axes accelerometers or a single tri-axial accelerometer can be used to obtain acceleration along the X, Y and Z directions. The microcontroller is not capable of sampling negative voltages and so, to facilitate that, the EEG signal is level shifted by a dc value before being fed into the amplifier. Since the EEG signal levels are typically in the range of 5- 50uV, a high impedance biomedical signal amplifier is used to amplify the signal by a value of the order of a few thousands. The amplifier used, supports variable gains from values of 1700 to 5000. A value of 2000 was used for our experiments. The amplified output is fed into the microcontroller. The level-shifting voltage value used is also sampled by the microcontroller. The pulse oximetry module is interfaced with the microcontroller through the serial port and the oxygen saturation and heart rate values are obtained in digital format and so, no processing is required.

The frequency at which these signals are sampled depends on the frequencies of interest. The frequencies of the EEG signals and accelerometer waveforms influence the minimum sampling rate. Since the accelerometer readings are instantaneous measurements of acceleration and since no frequency band decomposition is carried out, we will focus on the frequencies of interest in the EEG signals which are in the 1 – 70 Hz. However, since the metrics we utilize rely only on information in the alpha and theta bands, the maximum frequency in the bands of interest is 12 Hz and so the sampling frequency should be greater than 24 Hz. A value of 64 Hz is chosen. Sampling within the microcontroller can be carried out by using timers to trigger the conversion process within the ADC or by setting the ADC to continuously sample the data from the sensors and then using timers to read the digital values at the sampling frequency. The former approach is used as it is more consistent with the idea of sampling. Two timers are used to generate a 64 Hz waveform which is used to enable conversions within the ADC module.

Since we need to extract information contained within the various frequency bands of the EEG waveforms, we use

21 point symmetric Finite Impulse Response (FIR) filters. The coefficients for the filters are pre-computed using MATLAB and saved in the microcontroller. A 21 point value was chosen as a tradeoff between precision and computational space. A higher precision filter could have been used at the expense of higher storage space requirements (each coefficient is a floating point value) without considerable improvements in the quality of the filtered output. Another important consideration is the epoch or time window over which the calculations are made. While it is desirable to make decisions over a relatively long period of time, the memory space requirements impose a burden because of the limited memory space within the microcontroller. A value of 12 seconds was chosen to be length of the time window. While the measurements made are dependent on the length of the time interval, eventually a comparison is carried out with reference to a baseline value computed over the same time interval for every individual. This offsets the impact of the length of the selected time window. All the metrics are computed over the duration of this 12 second window.

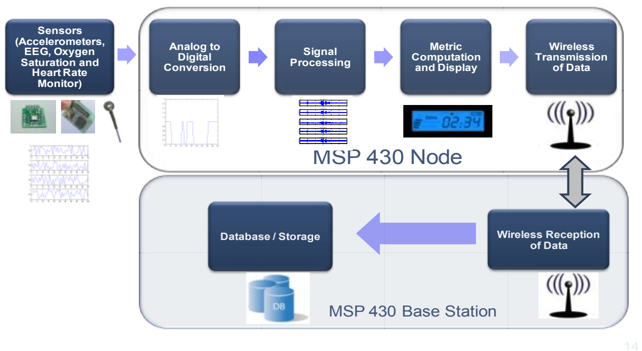

Figure 1: Working of Biomedical Monitoring System

The entire system operates as shown in Figure 1. Once the module is switched on, it computes the baseline/at rest values for metrics pertaining to each of the sensor values. Then the module goes into a monitoring mode, which can be continuous or event-triggered. In the continuous monitoring scheme, data from the sensors are collected and metrics are computed on a continuous basis. In the event-triggered monitoring scheme, an external event is used to trigger the monitoring process. One example of such an event could be an accident resulting in sudden acceleration of the individual which would show up as a spike in the accelerometer reading. This spike can then be used to shift the module in the continuous monitoring mode. Such a scheme can be used in extremely power-constrained environments. Once the data is obtained, the results of the computation process are then wirelessly transmitted to the base station which is another MSP430 node connected via the serial port to the PC. A Perl program reads the data from the serial port and logs the data into a MySQL database.

VI. EVALUATION

The EEG data on which analysis is carried out originate from a person who suffered a seizure. One minute of ictal data is available using the simulator. The primary indicator of a seizure is an increase in the amplitude of the low frequency theta waves with a simultaneous decrease in the amplitude of the higher frequency alpha waves. Since power is directly proportional to the square of the amplitude, the power contained in each frequency band can be computed over the duration of the data collection period (i.e., 12s in our study). The metric that is used to detect abnormalities in the EEG waveform is therefore, the *alpha-theta* ratio.

The *alpha- theta ratio* can be defined as the ratio of the power in alpha frequency band to the power in theta frequency band. When a seizure is observed, the alpha-theta ratio for that individual should be lower than the base/normal value established for that person. Figure 2 shows the alpha wave during the 12 second pre-ictal and ictal periods and Figure 3 shows the theta wave during the same periods. Although, the ictal period shows a minor increase in the alpha wave amplitude, the theta wave amplitude increases almost 3 fold resulting in an overall decrease in the alpha-theta ratio.

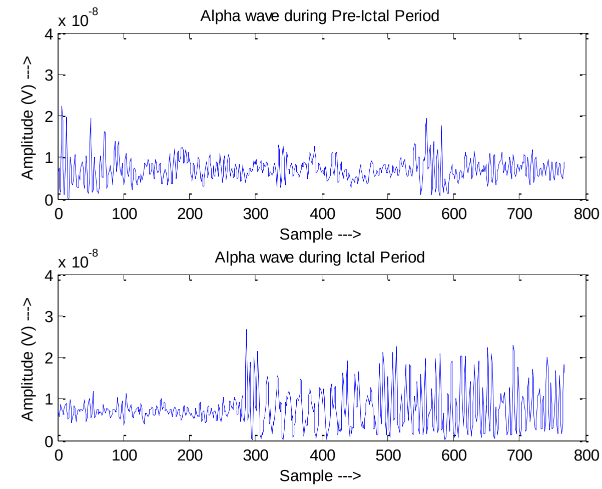

Figure 2: Alpha wave during Pre-Ictal and Ictal Periods

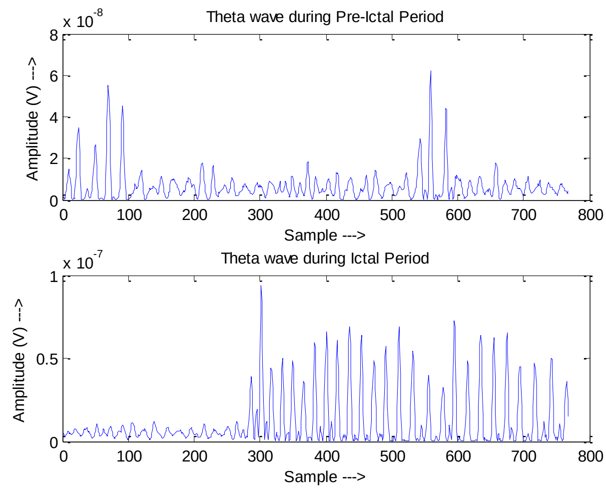

Figure 3: Theta wave during Pre-Ictal and Ictal Periods

Table 2 highlights the value of alpha-theta ratios computed from the one minute of EEG data obtained from the simulator. The lowest value in Table 2 is obtained when the continuous sequence of spikes are observed in the ictal waveform.

Table 2: Alpha-Theta Ratios of Ictal EEG

Reading	Alpha-Theta Ratio
1.	0.3477
2.	0.3464
3.	0.4456
4.	0.5127
5.	0.6040

As mentioned earlier, a poor neurological outcome is expected when oxygen saturation levels drop below 70%. Recent studies have also shown oxygen desaturation to be correlated with the occurrence of the seizure. Hence, a simple indicator of abnormal oxygen saturation levels would be a drop below 70%. Another indicator of abnormal health conditions would be a very low heart rate. If the heart rate drops to less than 75 percent of his base reading, it is inferred to be abnormal.

The metrics for each of sensor readings are summarized in Table 3.

Table 3: Metrics used for each sensor

Property being measured	Metric Name	Normal Value (with respect to baseline readings)	Abnormal Value (with respect to baseline reading)
EEG	Critical EEG	Above 50%	Less than 50%
Oxygen Saturation	Critical Oxygen	Above 70%	Less than 70%
Heart Rate	Critical Heart Rate	Above 75%	Less than 75%

All of the above individual metrics take a value of 1 under abnormal conditions and 0 under normal conditions as outlined in Table 3. These individual metrics can be combined linearly into an overall *Criticality Factor*, which indicates the level of critical injury suffered by the subjects. The *Criticality Factor* can be defined as follows:

Criticality Factor =
Critical EEG + Critical Oxygen + Critical Heart Rate (1)

Based on this formula, the value of Criticality Factor can assume 4 values from 0 – 3 and the conclusions drawn from each of those values are shown in Table 4. An indicator light, based on the Criticality Factor, is flashed for quick reference. A green LED is flashed to indicate normal conditions, a yellow LED is flashed for a possible abnormality, and a red LED is flashed for critical injury.

Table 4: Inference from value of Criticality Factor

Value for Criticality Factor	Inference
0	Individual is healthy
1	Abnormality only if Critical Oxygen is one and seizure if Critical EEG is one
2	Possible injury/seizure
3	Seek further medical care

VII. VALIDATION

In this section, we validate the use of the alpha-theta ratio metric we discussed in the previous section for EEG seizure detection. The waveforms plotted in Section 6 and the values for the alpha-theta ration indicated in Table 2 are based on the EEG data obtained from the EEG simulator. While this is actual ictal EEG, values obtained on the basis of a single test may not be conclusive enough to validate the use of the proposed metric for the seizure detection.

Since this study does not involve trials on human subjects, we perform the same processing on actual EEG data, collected from patients suffering from epileptic seizures stored in the EEG database at Albert-Ludwigs Universitat Freiburg, Germany. The database contains invasive EEG recordings of patients suffering from medically intractable focal epilepsy. The datasets are recorded during an invasive pre-surgical epilepsy monitoring. 24 hours of ictal and interictal EEG recordings are carried out. Experienced epileptologists visually inspected the intracranial recordings to determine the ictal periods based on identification of typical seizure patterns preceding clinically manifest seizures. The electrode positions are different for different people. Table 5 shows the values of the alpha-theta ratio calculated during the ictal periods and the value calculated during the inter-ictal period. The value obtained during the inter-ictal period is taken as the baseline value. Since the data is available in digital format, a MATLAB program performing the same processing as the microcontroller is used to obtain the values shown in the Table 5.

As can be seen in Table 5, there is a significant decrease in the alpha-theta ratio in almost all of the readings analyzed. Seizure 2 of the 14 year old patient showed the maximum change with an ictal alpha-theta value o f0.1828 while the baseline value was 0.9296. However in some of the readings a value close to baseline value is seen, although it is smaller than the baseline value. For example, seizure 3 gave a value of 0.76 during the ictal period for the 15 year old female patient, which is close to the baseline value of 0.7804. There could be several reasons for this behavior which cannot be inferred without obtaining additional information about the other conditions of the patients. This validates the use of the metric for seizure onset detection. Figure 4 and Figure 5 show two ictal-seizure patterns that were observed along with the alpha-theta value obtained. The ictal period, similar to the one obtained from the simulator (used in our measurements) shows an increase in the amplitude (or spikes) and a decrease in the alpha- theta value over the baseline values.

Table 5: Alpha Theta values for patients suffering epileptic seizures

Patient Information	Seizure Number	Baseline Alpha-Theta Value	Ictal Alpha-Theta Value
15 year old female	1	0.7804	0.4575
	2	0.7804	0.54
	3	0.7804	0.76
14 year old male	1	0.9296	0.2560
	2	0.9296	0.1828
32 year old female	1	1.3943	0.2786
	2	1.3943	1.0228
	3	1.3943	0.9208

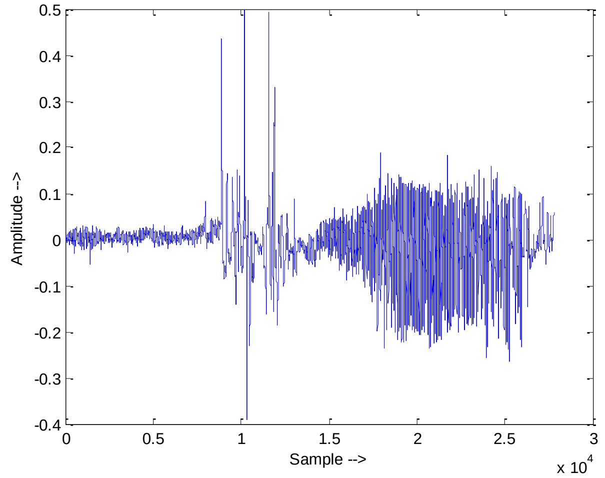

Figure 4: Seizure Pattern 1-Alpha –Theta Ratio = 0.2560

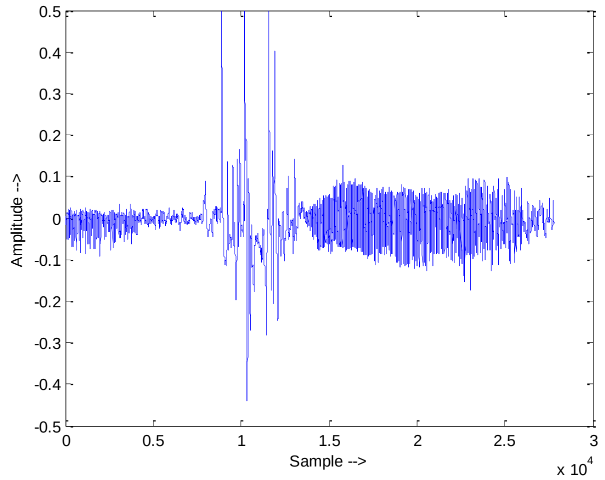

Figure 5: Seizure Pattern 2 -Alpha –Theta Ratio = 0.4575

VIII. APPLICATION SCENARIOS

Primary targets for the proposed system are environments where there is a potential risk of brain injury, e.g., the battlefield or high-speed car racing. The light weight and low power requirements make it feasible to embed the device in the protective head gear. For example, in our demonstration of the prototype device we instrument the soldier helmet by embedding the sensors and the processing element into the pads provided within the helmet [18]. Real-time monitoring of a soldier's physiological responses could help gain insight into occurrences of TBI. An earlier study indicated that approximately 10% of the individuals with TBI experience new onset seizures with the risk increasing with increased injury severity. Generalized complex seizures occur in approximately 33% of the cases [19]. Thus, the detection scheme used for detecting TBI could be similar to the one used in our device for identifying seizures. The use of real-time EEG monitoring to detect mild traumatic brain injury by embedding devices in football helmets is proposed in [20].

Another application scenario is continuous patient monitoring where each patient could be connected to a device such as the one proposed in this study. This will allow continuous collecting of relevant data, sending the data to the monitoring base station for logging and further processing. Furthermore, the light weight, the low cost, and the ease of operation make the device usable at a patient's home. In such a scenario, the base station would be smaller equipment with wireless communication capability and flash memory for data storage. An additional facility would be to alert the patient's physician via a Bluetooth module provided in the base station. In case of an emergency, the device could be programmed to send a message using the Bluetooth interface to the patient's mobile phone and then as a text message to the physician. The ability to communicate with the embedded processing equipment wirelessly and alert the physician, as described above, can be integrated seamlessly if a smart mobile phone with Bluetooth connectivity is used as the base station.

The system thus can be adapted to suit the requirements of the application as long as the symptoms being checked for are known and sensors are available for detecting the same.

IX. DISCUSSION

The system presented in this paper is capable of real-time collection of physiological data from multiple sensors synchronously and online signal processing to extract relevant metrics in order to make detection decisions. While the results are encouraging, further research is necessary because the analysis in this study was performed on simulated or readily available data. Further research should include extended EEG recordings of several patients. This research would further validate the existing detection system and possibly identify other indicators of abnormalities which would further improve the existing detection system. Additional research would also provide information about why some of the seizure cases analyzed from the EEG database, had ictal EEG alpha-theta ratios that were close to the baseline values.

Metrics. The prospect of coming up with other metrics to make the detection scheme more robust cannot be brushed aside. One important biometric that could prove to be useful in future analysis is *coherence*.

Coherence, $C_{xy}(f)$ between two waveforms can be defined by the following expression

$$C_{xy}(f) = |P_{xy}(f)| / (P_{xx}(f).\ P_{yy}(f)) \qquad (2)$$

where Pxy(f) is the cross-power spectral density of x and y, Pxx(f) and Pyy(f) are the power spectral densities of x and y respectively. Coherence values range from 0 to 1.

The coherence across the alpha frequency band is used for studies related to cognitive decline. However, it is a complex function to be computed using a microcontroller during the course of time window while meeting the real-time requirements. This issue is addressed in the discussion on the future work.

Sensor connectivity. An important aspect to take into consideration is the quality of the sensors which are used to collect the measurements. In particular, ensuring uninterrupted connectivity (in particular for the noninvasive sensing such as measurement of EEG and ECG) can be a major problem. For example, there is no easy way to distinguish between a sampled value obtained under normal conditions (i.e., under good connectivity) and values obtained when the sensor is disconnected from the ADC inputs. Another similar case would be maintaining connectivity between the EEG electrodes and the forehead or the pulse oximeter sensor and the skin. Traditional Ag/Cl electrodes can prove to be a problem even if used with a suitable adhesive like an EEG paste. There is considerable focus on developing electrodes which are capable of measuring electrical activity consistently even if there is a minor loss of connectivity between the surface of the skin and the electrode. One such effort would be the use of unique optical voltage sensing technology to measure and monitor electrophysiological parameters. This technique obviates the use of conductive gels to measure EEG signals [17].

Sensor failures. Failure of sensors during operation is a topic which requires attention too. When dealing with analog sensors, it is quite difficult to detect failures unless the condition of operation in failure is significantly different from the normal expected operating conditions. For example, the accelerometers used in our study give a baseline reading of around 1V at rest and depending on the direction of acceleration, the voltage increases or decreases. It may be quite difficult to know when the sensor has actually failed unless the voltage reading consistently stays close to the maximum or minimum observable value. However, this problem can be overcome by using redundant sensors. If the readings from the multiple sensors show a significant difference we know that there is a problem. In order to circumvent this, we can use a majority voting technique with a predefined tolerance value to obtain the actual sensor reading.

Reliable and secure operation. Another important consideration is the reliability and security implications posed by such a device, especially when operated under extreme conditions. Reliability of the device is essential for enabling robust autonomous operation and trustworthy decision making process. A simple hardware based reliability solution would be to introduce redundancy of hardware modules to account for failures or to introduce voting in the decision making stage of the device before making a conclusion about the health status of the individual. For this purpose, a reconfigurable hardware based implementation would provide a suitable platform. With the development of mixed signal FPGA platforms such as Fusion from Actel, future work would focus on development of a reconfigurable embedded system that provides redundant sensors and hardware based signal processing primitives for a fast and reliable processing.

Since communication capabilities are an important part of the device, the question of security is an important one that has to be addressed. Most hardware platforms currently provide for hardware based encryption which is significantly faster and power efficient than its equivalent software counterparts.

The outlined design provides more powerful processing element, which can enable on-line computation of more complex metrics such as the coherence, which is computationally intensive and memory "hungry". Some of the previous studies have used complex processing techniques like wavelet transforms to process EEG waveforms [9]. Wavelet transforms are computation intensive and usually cannot be accomplished using a simple microcontroller. Our future work will focus on exploring novel processing techniques and defining new metrics. Towards this we will explore using FPGA-based platforms for rapid prototyping and testing. The resulting designs can be than implemented as SoC (system on a chip).

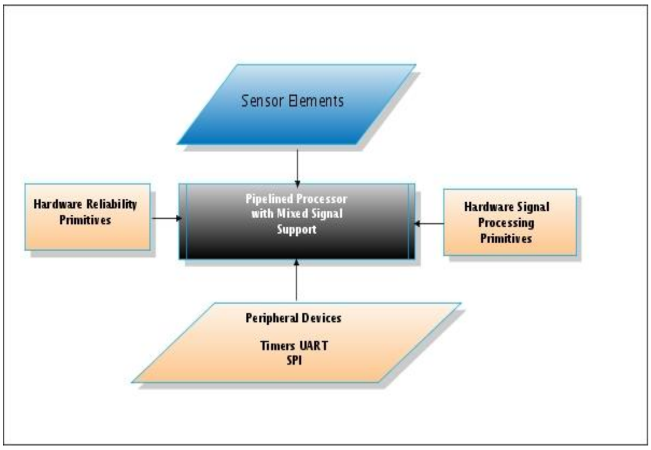

Figure 6: Mixed Signal FPGA Implementation

X. CONCLUSION

The embedded system described in this paper provides a platform that is capable of collecting data from multiple sensors and performing real time analysis on the data to compute metrics that help in identifying symptoms/ abnormalities previously studied corresponding to the sensor readings. Specifically we have used this device to detect epileptic seizure patterns in EEG activity based on quantitative EEG analysis. The device has a very small footprint and is extremely compact, making it suitable for an eventual SoC implementation.

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REFERENCES

[1] G-Z. Yang, *Body Sensor Networks*. Springer, 2006.

[2] R.K. Ganti, T.F. Abdelzaher, P. Jayachandran, J.A.. Stankovic, "SATIRE: A Software Architecture for Smart AtTIRE," *Proceedings of 4th International Conference on Mobile Systems, Applications, and Services, Mobisys '06*, June 2006.

[3] L.M. Hively, N.E. Clapp, V.A. Protopopescu, J. Joseph, C.E. Merican, T. Lucht, *Epileltic Seizure Forewarning by Nonlinear Techniques*. Oak Ridge, TN: Oak Ridge National Labs, 2000.

[4] A. Shoeb, S. Schachter, T. Pang, and J. Guttag, "Implementation of closed-loop, EEG-triggered vagus nerve stimulation using patient-specific seizure onset detection from scalp EEG," *American Epilepsy Society 61st Annual*, Meeting, December 2007.

[5] A. Shoeb, S. Schachter, B. Bourgeois, S.T. Treves, and J Guttag. Impact of Patient-Specificity on Seizure Onset Detection Performance *29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, August 2007*.

[6] N. Verma, A. Shoeb, J. Guttag, and A. Chandrakasan, "A micro-power EEG acquisition SoC with integrated seizure detection processor for continuous patient monitoring," *2009 Symposium on VLSI Circuits,* June 2009.

[7] B. Liu, Y. Zhang, Z. Liu, and C. Yin, "An embedded EEG analyzing system based on uC/os-II," *Proceedings of the 29th Annual International Conference of the IEEE EMBS,* August 2007.

[8] Yitzhak Mendelson. Wearable Devices for Real-Time physiological monitoring, Dept of biomedical Engineering, Worcester Polytechnic Institute

[9] T. Malina, A. Folkers, and U.G. Hoffman, "Real-time EEG processing based on wavelet transformation," *12th Nordic Baltic Conference on Biomedical Engineering*, June 2002.

[10] A.K. Gupta, "Monitoring the injured brain in the intensive care unit," *Journal of Postgraduate Medicine*, vol. 48, no. 3, pp. 218-225, July-September 2002.

[11] B. Wallace, A. Wagner, E. Wagner, and J. McDeavitt, "A history and review of quantitative electroencephalography in traumatic brain injury," *J Head Trauma Rehabil,* vol. 16, no. 2, pp. 165-190, 2001.

[12] K. van der Hiele, A.A. Vein, R.H.A.M. Reijntjes, R.G.J. Westendorp, E.L.E.M. Bollen, M.A. van Buchem, J.G. van Dijk, and H.A.M. Middelkoop, "EEG correlates in the spectrum of cognitive decline," *Clinical Neurophysiology,* vol. 118, no. 9, 1931-1939, 2007.

[13] R. Thatcher, D. North, R. Curtin, R. Walker, C. Biver, J. Gomez, and A. Salazar, "An EEG severity index of traumatic brain injury," *J Clinical Neuropsychiatry,* vol. 13, no. 1, pp. 77-87, Winter 2001.

[14] S. Ahmad, G. Grindlinger, and S. Desjardins. "Noninvasive cerebral oximetry in patients with traumatic brain injury (TBI)," *Critical Care Medicine*, vol. 32, no. 12 (Suppl.), p. A104, 2004.

[15] C.M. Dunham, K. Ransom, C. McAuley, B. Gruber, D. Mangalat, and L. Flowers. "Severe brain injury ICU outcomes are associated with cranial-arterial pressure index and noninvasive bispectral index and transcranial oxygen saturation: a prospective, preliminary study," *Critical Care,* vol. 10, no. 6, pp. R159-R168, November 2006.

[16] L.M. Bateman, C-S. Li, and M. Seyal, "Ictal hypoxemia in localization related epilepsy: analysis of incidence, severity and risk factors," *Brain*, vol. 131, pp. 3239-3245, December 2008.

[17] B. Wahlund, P. Piazza, D. von Rosen, B. Liberg, and H. Liljenstrom, "Seizure (Ictal) – EEG characteristics subgroup depressive disorder in patients receiving ECT – a preliminary study and multivariate approach," *Computational Intelligence and Neuroscience,* in press.

[18] A. Cheriyan, A. Jarvi, Z. Kalbarcyzk, R.K. Iyer, and K.L. Watkin, "Pervasive embedded systems for detection of traumatic brain injury," *Proceedings of 2009 IEEE International Conference on Multimedia and Expo, ICME 2009,* unpublished.

[19] J. Meythaler and T. Novack, "Post traumatic seizures following head injury," *UAB Traumatic Brain Injury Model System*, http://main.uab.edu/tbi/show.asp?durki=10213&site=2988&return=49704, Accessed 9 June 2009.

[20] R.W. Thatcher, "Electroencephalography and mild traumatic brain injury," in *Foundations of Sport-Related Brain Injuries*, Springer, 2006.

[21] S.A. Kingsley, S. Sriram, A. Pollick, J. Marsh, "Revolutionary optical sensor for physiological monitoring in the battlefield," *Proc. SPIE*, vol. 5403, pp. 68-77, 2004.